

**The changing geography of health inequalities:
A spatial exploration of area deprivation
and Limiting Long-Term Illness across Britain**

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**No more the drudge and idler, ten that toil where one reposes,
But a sharing of life's glories; give us bread, but give us roses.**

Extracts from *Bread and Roses*, original poem by James Oppenheim, (1911). *American Magazine*.

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Abstract

Socioeconomic gradients in health which manifest geographically are well documented in Britain but remain poorly understood. Although the study of variations in health has a long history, exploring the changing spatial structure of health in Britain has previously been limited by inconsistent spatial data which do not permit comparability over time. To date, most geographically-focused health inequalities research has relied on conventional non-spatial methodologies and there are very few studies of how geographical circumstances throughout time influence health outcomes. The value of this thesis derives from its exploitation of consistent geographical zones which permit comparisons across space and over time. Through documenting the long-term unevenness of characteristics and the resulting inequalities in health between localities, this thesis offers a new level of insight into changing population health and geographic inequalities for the whole of Britain which has not previously been available. This thesis utilises consistent 1km² spatial units to examine the changing spatial structure of self-reported health in Britain, 1991 to 2011, against a backdrop of 1971 to 2011 area deprivation and social indicators. It applies an explicitly spatial approach to identify how the long-term geography of socioeconomic inequality is associated with changing health variation in Britain.

Through accounting for spatial structure the analysis provides a detailed representation of the influence of deprivation for understanding health inequalities across Britain. Results demonstrate the extent to which the socioeconomic history of local areas matter for health, highlighting that long-term economic inequalities play a significant role in the divergent health profiles of different places. The impact of deprivation for health is not evenly spread across Britain, but is instead revealed to be spatially concentrated. The substantive issue of whether Britain has become more segregated by health status through time is also addressed with findings demonstrating that inequalities in health have grown across spatial dimensions over time.

An understanding of the changing spatial structure of health in Britain, the association between deprivation and spatial inequalities in health, the drivers of these associations, and the importance of historical factors in shaping contemporary patterning of health inequalities is demonstrated through the findings presented in this thesis. Such knowledge can help to inform targeted policies aimed at reducing health inequalities, offering potential for improving health outcomes across the social gradient, but particularly amongst the most disadvantaged groups.

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List of abbreviations

AIC	Akaike Information Criterion
CATTs	Consistent Areas Through Time
DEFRA	Department for Environment, Food and Rural Affairs
DHSS	Department of Health and Social Security
DFLE	Disability-free Life Expectancy
ESRC	Economic and Social Research Council
EDs	Enumeration Districts
GP	General Practice
GIS	Geographic Information Systems
GWR	Geographically Weighted Regression
HIE	Healthy Immigrant Effect
HMOs	Houses in Multiple Occupation
IMD	Index of Multiple Deprivation
UPA	Underprivileged Area
JRF	Joseph Rowntree Foundation
LE	Life Expectancy
LLTI	Limiting Long Term Illness
LADs	Local Authority Districts
LISA	Local Indicators of Spatial Association
MSOA	Middle-Layer Super Output Areas
MAUP	Modifiable Areal Unit Problem
NHA	National Health Service
NIRSA	Northern Ireland Statistics and Research Agency
ONS	Office for National Statistics
OLS	Ordinary Least Squares
OA	Output Area
PHE	Public Health England
QC	Queen Contiguity
SMF	Social Market Foundation
UK	United Kingdom
US	United States
UDHR	Universal Declaration of Human Rights
VIF	Variance Inflation Factors
WHO	World Health Organisation

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Chapter 1

Introduction

1.1 Introduction

The opportunity to live a long and healthy life remains profoundly unequal. Socioeconomic gradients in health which manifest geographically are well documented within Britain and are some of the largest in Europe, but remain poorly understood (Acheson, 1998; Macintyre et al., 2005; Marmot, 2010, Whitehead, 2014). There is considerable interest in understanding how the nature of such inequalities have changed over time. This thesis focuses on developing an understanding of the changing spatialities of health inequalities. It details a novel analysis of change over small areas of Britain from 1971 to 2011, identifying how the long-term geography of socioeconomic inequality is associated with changing health variation.

Spatial health inequalities are problematic. They cannot be accounted for by differences between population groups and indicate marginalisation of certain populations and places (Dahlgren and Whitehead, 2007). It is well established that health outcomes generally worsen in line with greater levels of socioeconomic disadvantage; in what is termed the ‘social gradient’ of health (Marmot, 2010). Those in the most socioeconomically advantaged positions have the best health, and those with the most deprived circumstances have the poorest (Benzeval et al., 2014). Social and spatial health polarisation is not inevitable and reducing persistent health inequalities is an important objective in Britain. The lack of understanding about how the spatialities of health change over time challenges progress in delivering interventions to flatten disparities. While clear geographic patterning to the social gradient is established, the way in which demographic, socioeconomic and spatial factors interact over time to create the distinctive geography of health inequalities observed is less well understood.

A detailed understanding of how inequalities manifest spatially is important for the success of initiatives to address them, both in terms of the nature of the initiatives and their geographical

targeting. Having transparent and robust mechanisms for prioritisation and action is essential, especially given current pressures on public spending in Britain. New conceptual and methodological work that examines the dynamic histories of places and the implications of this temporal evolution for geographies of health is required to help understand the determinants of these patterns (Lekkas et al., 2017; Pearce, 2018). An approach which incorporates area histories and explores how health at one point in time is influenced by conditions at a previous time point can offer a more complete understanding.

1.2 Rationale

There is a strong and persistent link between broader political, social and economic structures and disparities in health outcomes (Marmot, 2010). In Britain, the period 1971 to 2011 has been one of considerable demographic and socioeconomic change. Over this period the composition of the population has undergone a marked transformation. In line with a general trend around the world, life expectancy in Britain has risen (Office for National Statistics [ONS], 2018). This has meant the average age has increased, a process accentuated by the extent to which the birth rate has remained low (ONS, 2012). Furthermore, large scale immigration to Britain over this period, particularly from the West Indies, South Asia and Eastern Europe, has contributed to a more ethnically diverse population (Public Health England [PHE], 2017). In Britain, deindustrialisation took place rapidly in the 1970s and 1980s accompanied by rising unemployment in many areas once dominated by manufacturing, coal mining and ship building industries (Taulbut et al., 2014). Additionally, as foreign travel became more accessible, domestic tourism destinations also experienced decline over this period (Corfe, 2017). Through influencing underlying disparities in the wider determinants that impact upon health, such demographic and socioeconomic transformations are likely to have important implications for understanding geographical inequalities in health (Dahlgren and Whitehead, 2007).

Although the study of variations in health has a long history, exploring the changing spatial structure of health in Britain has previously been limited by inconsistent spatial data which do not permit comparability through time. To date, most studies on the relationship between health and place have relied on cross-sectional analyses and there are very few studies of how geographical circumstances throughout time influence health inequalities. The value of this thesis derives from its exploitation of consistent geographical zones which permit comparisons across space and over time. The gridded data on which this thesis is based were generated as a part of the ‘PopChange’ project (Lloyd et al., 2016, Lloyd et al., 2017a). This

data provides the first consistent small area Census dataset for 1971 to 2011 and consequently enables a direct time-series analysis of the spatial relationship between health outcomes and area deprivation. Through documenting the long-term unevenness of characteristics and the resulting inequality in health between localities, this work offers a new level of insight into changing population health and geographic inequalities for the whole of Britain which has not been available before.

Recognising that a relational place-based approach is fundamental in furthering understanding of health inequalities this work is explicitly spatially focussed. Drawing on methodological developments and advances in the availability of consistent data, the geographical approach this thesis takes is novel. Considering socioeconomic attributes at a specific point in time, and assessing the relationship to health in subsequent years, this work offers a long-term approach to understanding how health inequalities in Britain manifest spatially. Although there are some exceptions (for example, Exeter et al., 2005; Norman and Riva, 2012), most previous research that explores geographic variation in health has focused on cross-sectional analysis (Dorling et al., 2000; Gregory, 2009). Single-point-in-time analyses may overlook processes of change or resilience that embed contemporary health inequalities within locales (Lekkas et al., 2017).

By explicitly recognising that places are spatial-temporal products this thesis considers historical and geographical dimensions, exploring the changing landscape of health outcomes over time. It is possible to begin to unpick how changes in deprivation and other characteristics of populations relate to health status by measuring how much poor health has changed in areas over several decades, or by identifying persistence of poor health clusters. Findings from this thesis will make important contributions to further work that strives to understand temporal dynamism in shaping the spatialities of health inequalities.

1.3 Aims and Objectives

This thesis seeks to capture the diverse nature of changing health inequalities at a geographically detailed scale and provide quantitative evidence that can be utilised in future work to explore the nature of this patterning. To achieve this, the aims of this thesis have been identified as:

- I. Explore the changing spatial structure of health in Britain 1991 to 2011**
- II. Understand the association between deprivation and spatial inequalities in health.**

- III. Apply spatially explicit methods to disentangle the drivers of geographical inequalities in health.**
- IV. Examine the importance of historical deprivation for the spatial patterning of health.**

Developing quantitative knowledge about the spatial expansion and persistence of poor health is critical to developing effective ways of tackling inequalities. **Aim I.** explores trends in Limiting Long-Term Illness (LLTI) for small areas 1991 to 2011, charting how inequalities in Britain have changed over time. Before the processes which contribute to changing spatial health inequalities can be explored comprehensively it is first important to gain a detailed understanding of how health has been spatially structured over time. Being able to measure change in health inequalities is crucial in assessing whether the population has become more or less similar over time and how it is geographically organised. The utilisation of 1km² units offers a geographically fine-grained level of spatial detail few previous investigations have been able to offer.

Once the changing spatialities of health has been established (aim I.) **aim II.** begins to understand why these inequalities exist. Using each of the Census periods, the thesis will analyse the association between local area deprivation and health outcomes. Whilst the evidence for this association is well-established, few studies have explored this association over the long-term or with national level population coverage. The thesis will not only focus on the overall level of deprivation, but by additionally unpicking the relative contributions of deprivation components a greater understanding of the specific pathways through which disadvantage impacts health will be obtained. Analyses will also consider the role of population characteristics including age, ethnicity and country of birth.

Recognising the additional insight and understanding a relational geographic approach can provide **aim III.** extends the analyses introduced in aims I and II through applying spatially explicit methods. The investigation of spatial inequalities is commonly accompanied throughout the literature with statistical approaches that fail to account for the ‘spatial’ aspect of patterns. As outlined by Tobler’s (1970) First Law of Geography, areas that are located closer together are more likely to be similar than those further apart. Ignoring the spatial structure to areas may produce biased or misleading results that will limit understanding of the determinants of health inequalities. This thesis utilises spatial and geographically-

weighted regression techniques to extend classical non-spatial modelling approaches and gain detailed insights into the changing spatial structure of health inequalities in Britain.

Leveraging the temporal approach of this thesis, **aim IV.** builds on the associations established in aims II. and III to examine how the spatial patterning of health in one time period is related to deprivation characteristics in previous periods. This also allows for novel analyses of associations between the persistence of poor health and deprivation more generally. A long-term approach to understanding how health inequalities in Britain manifest spatially in relation to underlying demographic and socioeconomic characteristics makes valuable new contributions. Examining the dynamic histories of places is key to illuminating the processes through which spatial inequalities in health are being maintained and how they might be successfully reversed.

To achieve these aims, the following research objectives have been identified. Although all the objectives complement each aim, the aim with which the specific objective engages is given in brackets. The chapter(s) where this objective is addressed is also provided for clarity:

1. Review literature to comprehend the socioeconomic and geographical determinants of health and their interdependence to (changing) health inequalities [Aims I, II, III and IV, Chapter 2].
2. Determine the availability of consistent health and demographic data between 1971 and 2011 [Aims I, II, III and IV, Chapters 2 to 5].
3. Identify small scale geographical patterns of health for Britain [Aim I, Chapter 3].
4. Examine how the patterning of LLTI has changed between 1991 and 2011 [Aim I, Chapter 3].
5. Explore the social and geographical determinants of health inequalities [Aims II and III, Chapters 4 & 5].
6. Analyse the role of historical contextual factors in explaining contemporary health patterns [Aim IV, Chapter 4 & 5].
7. Extend global regression approaches to incorporate a spatially explicit modelling framework [Aim III, Chapters 4 & 5].

1.4 Thesis Structure

This thesis takes the PhD by publication pathway and is comprised of six chapters. Following this introduction (Chapter 1), Chapter 2 explores the theoretical framework in which this

research is set. Whilst a discussion of the literature particularly pertinent to each analytical chapter is undertaken on a chapter-by-chapter basis, Chapter 2 importantly sets the general context for this thesis. The following themes are focused on: understanding health inequalities; the impact of deprivation on health; the importance of taking a geographical approach; the mechanisms through which geography can affect health. Chapter 2 also investigates applications of spatially focussed methodologies specifically from a health inequalities perspective including investigating the challenges of change over time. The chapter ends by discussing gaps in the literature which this thesis seeks to address.

Chapter 3 investigates the changing spatial distribution and clustering of LLTI across Britain over time. New insights are obtained in this work by examining the changing distribution (evenness and clustering) of health over time through an area classification framework. In evidencing the geographies of health inequalities over time, this paper makes unique contributions to understanding the formation and impact of health inequalities and their wider geographies. The results presented examine the nature of the spatial structure of health in Britain, suggesting that neighbouring areas are becoming more similar. This chapter is based upon: Dearden, E, K., Lloyd, C, D. and Catney, G. (2019) A spatial analysis of health status in Britain, 1991-2011. *Social Science & Medicine* 220, pages 340-352. The analysis and writing for this paper were undertaken by Dearden; advice, guidance and editorial support were provided by Lloyd and Catney.

In seeking to understand the influence of place on health, the role of deprivation is crucial. Analysis in Chapter 4 investigates the nature of the association between health and deprivation. Recognising how differences in health are perpetuated through broader socioeconomic and spatial inequalities is a vital step in addressing unequal health outcomes within Britain. This ecological analysis examines changing health inequalities across Britain, providing insights into the extent to which area histories matter for health. Considering changes over time, the results highlight the enduring effect of historical conditions on health and suggest that area histories are likely to matter more in certain areas and at certain times. Chapter 4 is based upon the following paper: Dearden, E, K., Lloyd, C, D. and Green, M., Exploring the histories of health and deprivation in Britain, 1971 to 2011 currently under review at *Health & Place*. The analysis and writing for this paper were undertaken by Dearden; advice, guidance and editorial support were provided by Lloyd and Green.

Chapter 5 takes an explicitly spatial approach to identify how the long-term geography of socioeconomic inequality is associated with changing health variation in Britain. This is achieved through the use of Geographically Weighted Regression (GWR) approaches. The results provide useful insights into where and how the relationship between independent determinants and health outcomes vary temporally and by geographical location, enhancing understanding of the interconnection between health and deprivation in specific ways. Findings point to the need to understand the heterogeneity of area level health determinants. Chapter 5 is based upon the paper: Dearden, E, K., Lloyd, C, D. and Green, M., Exploring spatial variability in changing health inequalities: area deprivation and Limiting Long-Term Illness across Britain in 1991 and 2011, currently under review at *Social Science & Medicine*. The analysis and writing for this paper were undertaken by Dearden; advice, guidance and editorial support were provided by Lloyd and Green.

The thesis is concluded in Chapter 6. A summary of research findings is firstly outlined, focussing on how the thesis has successfully addressed each of the aims and objectives which frame this research. The limitations of the thesis are then discussed to critically evaluate the research findings presented. To further develop and extend the ideas discussed throughout this thesis, Chapter 6 ends by proposing future extensions of research based upon the findings and limitations presented.

1.4.1 Analytical Framework

Census data on Limiting Long-Term Illness are first recorded in 1991, consequently this thesis examines the changing spatial structure of self-reported health in Britain and over the period 1991 to 2011. The ‘PopChange’ resource also provides information on a wide range of variables which are comparable across Census from 1971 to 2011 where available. In seeking to disentangle the drivers of changing spatial health inequalities analysis utilises a backdrop of 1971 to 2011 area deprivation and demographic indicators. Figure 1.1 illustrates the Census data utilised in the analysis chapters of this thesis. The incorporation of variables relating to previous time points offers a long-term approach to understanding how health inequalities in Britain manifest spatially.

An approach which incorporates area histories and explores how health at one point in time is influenced by conditions at a previous time point can offer a relational understanding of health inequalities and their spatial manifestation. Identifying how the long-term geography of socioeconomic inequality is associated with changing health variation in Britain necessitates

the use of variables pertaining to different Census years. The value of this thesis derives from its exploitation of consistent geographical zones which permit comparisons across space and over time.

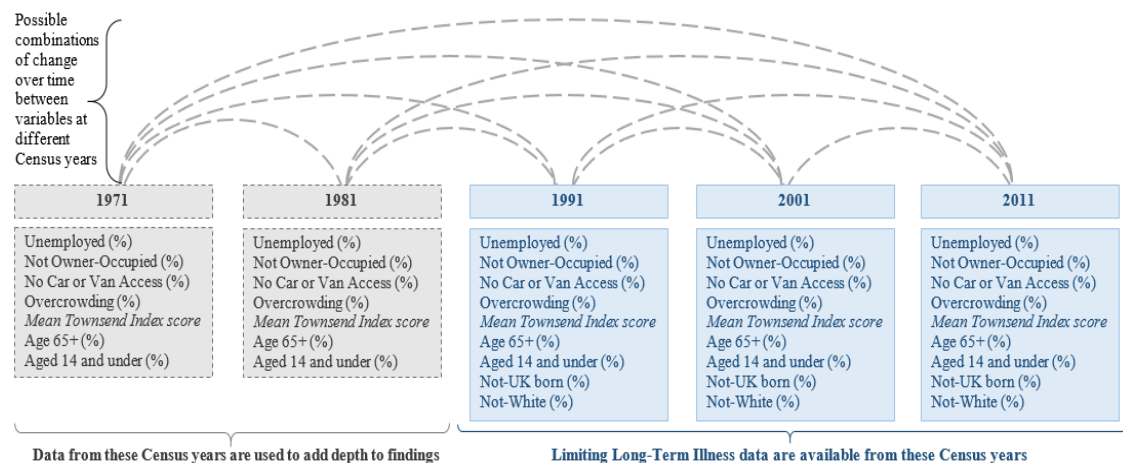


Figure 1.1: Analytical Data Framework

Through incorporating historical Census variables this thesis offers a long-term approach to understanding how the drivers of health inequalities in Britain manifest spatially. As outlined in Figure 1.1, for each year that health data is available (1991, 2001, 2011) there are three temporal periods for which variables that can be included in analysis are available:

- Variables recorded at the same Census year as the independent variable of analysis (LLTI).
- Variables recorded at a previous Census year to the independent variable of analysis (LLTI). For example, unemployment rate recorded at the 1981 Census included in a model to explore LLTI rates in 1991.
- Variables which represent change over time in rates between consecutive Census years (and for different temporal combinations over the five Census time points). For example, Unemployment change between 2001 and 2011 = Unemployment rate in 2011 minus Unemployment rate in 2001.

Details of the specific variables utilised in each analysis (and the time periods they relate to) are detailed in the relevant chapters of this thesis. Descriptive statistics of variables for each year that they are available are provided in Table 4.1 (page 108).

The incorporation of variables relating to previous time points offers a long-term approach to understanding how health inequalities in Britain manifest spatially. Through documenting the long-term unevenness of characteristics and the resulting inequalities in health between localities, this thesis offers a new level of insight into changing population health and geographic inequalities for the whole of Britain which has not previously been available. Results highlight that long-term spatial inequalities play a significant role in the divergent health profiles of different places.

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Chapter 2

Literature Review

2.1 Introduction

The literature review grounds the thesis in the context of broader investigations into understanding the determinants of geographical inequalities in health, particularly socioeconomic explanations for changing health gradients. It begins by defining and conceptualising health, discussing how it is investigated and collected in contemporary research. The discussion then turns to exploring the histories of health inequalities in Britain, looking to key literatures on the drivers of these inequalities and of the relevant conceptual debates. Methodological approaches for researching the spatial structuring of health including exploring changes over time are then considered. This chapter highlights the importance of taking a geographical approach to health research to further our understanding of spatial patterns and processes. It ends with some conclusions gathered from the review, identifying research gaps and opportunities which the thesis will aim to address.

2.2 Conceptualising health

While we all have an inherent grasp of what we believe health to be, defining what ‘health’ is has been the subject of many academic studies (Engel, 1960; Nordenfelt, 1995; Jadad and O’Grady, 2008; Huber et al., 2011). The earliest definition of health was introduced by the World Health Organisation (WHO) in 1946 which defined health as “a state of *complete* physical, mental and social well-being and not merely the absence of disease or infirmity” (1946, page 1, *emphasis added*). There are obvious difficulties with this definition. The need for complete well-being limits the practical use of the WHO’s definition of health in population health research, neither defining ‘well-being’ nor being applicable to an ageing population with a growing prevalence of chronic disease (Jadad and O’Grady, 2008; Huber et al., 2011). Further, this conceptualisation has led to logically measuring health by its absence; for example, through disease or mortality (Shaw et al., 2008; Hacking et al., 2011).

In the Ottawa Charter (1986) the WHO proposed moving away from viewing health as a state, toward a dynamic model that presents health as a process: “The extent to which an individual or group is able to realise aspirations and satisfy needs, and to change or cope with the environment” (Health Promotion International, 1986 page 1). This framing also recognises health as a resource with a focus on active participation in life and with an emphasis on social, personal and mental resources in addition to physical capacities (Health Promotion International, 1986). Moving beyond definitions of health as simply the absence of disease embraces the broader determinants of health that include the social, cultural, and physical environments, as well as individual lifestyle behaviours and is important from a health inequalities perspective (Marmot, 2010). Understanding health in these terms would define a ‘healthy individual’ not as someone free from disease, but as someone with the opportunity for meaningful work, secure housing, stable relationships, self-worth and healthy behaviours (Kearnes and Moon, 2002). Applying this definition to a health inequalities framework, a lack of employment opportunities and access to affordable housing might be framed as health problems, as such tackling these issues is necessary to promote the conditions for good health (Marmot, 2010).

2.2.1 Self-reported health

Many studies exploring health inequalities employ self-reported health as an outcome measure (Manor et al. 2001; Benjamins et al., 2004; DeSalvo et al., 2006; Cooper et al., 2015; Putrik et al., 2015). The popularity of this measure lies in its simplicity and ability to capture conditions that are poorly reflected by objective, disease-based approaches (Harding and Balarajan, 2001). Cooper et al. (2015) utilise self-reported health data in the United Kingdom (UK) context to explore the socioeconomic indicators that correlate most closely with poor health outcomes. Putrik et al. (2015) used self-reported general health data to establish an association between health and the quality of the residential environment in the Netherlands, finding a positive relationship between reporting poor health and negative neighbourhood features. Bécares et al. (2012) examined the association between area-level deprivation and the health status of different ethnic groups in the UK using self-rated general health data.

Self-reported measures are subjective, integrating personal expectations of health and experiences across the life course (Harding and Balarajan, 2001; Wu et al., 2013). As such, these measures may be affected by social, cultural, regional and temporal subjectivity and imprecision (Senior, 1998; Harding and Balarajan, 2001). Expectations of health are fluid through time and may be culturally and socially determined and influenced by comparisons

to other groups or individuals (Bardage et al., 2005; Jylha, 2009). Despite often having better objective health outcomes than men, women frequently report poorer self-reported health (Boerma et al., 2016). Societal gender inequalities have been postulated as an explanation for the gender gap in self-reported measures of health (Boerma et al., 2016). It is important to recognise the conceptual ambiguity of ‘health’ and not assume that what constitutes good health is universal (Huber et al., 2011); individual expectations of health vary according to cultural background and personal beliefs (Harding and Balarajan, 2001; Bardage et al., 2005) and socio-political and historical contexts (Hunt et al., 1991). When conducting population health research from a geographical perspective across a number of constituent countries influenced by various beliefs and characteristics, this recognition is particularly important (Bardage et al., 2005).

Previous studies have shown that self-reported health indicators are predictive of subsequent morbidity and mortality (Ider and Benyamini, 1997; Benjamins et al., 2004; Jylha, 2009; Wu et al., 2013; Putrik et al., 2015). Manor et al. (2001) examine differences in disease prevalence between individuals reporting to be healthy, relatively healthy or unhealthy. They demonstrate self-reported health to be strongly associated with serious health conditions such as epilepsy, cancer and diabetes, but also with lesser conditions such as eczema and hay fever (Manor et al., 2001). Similarly, Wu et al. (2013) find that self-assessed health (including different constituent components of measures of it) consistently correlate strongly with objective health data including hospital records.

The association between self-reported health and objective measures of health varies between populations and population sub-groups. Singh-Manoux et al. (2007) demonstrate that self-reported health is less predictive of mortality at older ages, more predictive of mortality in individuals of lower socioeconomic status, and has a stronger association with mortality for men than for women. These implications may affect the interpretation of any analyses exploring geographical inequalities in self-reported health. For example, socioeconomic differentials in self-reported health and mortality were larger in Northern Ireland than in Scotland or England and Wales, demonstrating the importance of considering local context in analyses (Bardage et al., 2005).

Limiting Long-Term Illness (LLTI) is one commonly used self-reported health measure and was first included in the Census of England and Wales, and Scotland in 1991. In the most recent Census the measure asked “Are your day-to-day activities limited because of a health

problem or disability which has lasted, or is expected to last, at least 12 months? Include problems related to old age” (Office for National Statistics, 2013). While the wording of this question may encourage respondents to only assess their physical health, excluding broader psychosocial aspects of mental and social well-being, it has been used widely as a valid measure of health status (Cohen et al., 1995). LLTI data have been used to facilitate research on a broad range of topics, including area level health resilience (Cairns et al., 2012), small area health need profiling (Congdon, 2006), selective sorting (Boyle et al., 2004) and health gradients (Harding, 2003; Norman et al., 2011).

2.3 Health inequalities

Health is a fundamental human right, recognised in the Universal Declaration of Human Rights (UDHR) (United Nations, 1948). Developed under this view the National Health Service (NHS) was created in the UK in 1948, providing universal healthcare free at the point of use (Beveridge, 2000). The NHS created a provision of health services to meet a long recognised need and tackle issues of inequality that dominated post-war society; want, disease, idleness, squalor and ignorance (Beveridge, 2000; Rivett, 1998). Despite expectations that health inequalities would decline with the introduction of the NHS, evidence points to persistent socioeconomic differences across a wide range of health measures (Department of Health and Social Security ([DHSS], 1980; Marmot et al., 1991; Macintyre et al., 1993; Acheson, 1998; Cummins et al., 2007; Chandola et al., 2007; Marmot, 2010). Evidence has demonstrated inequalities by specific morbidities such as cardiovascular disease (Mackenbach et al., 2000; Diez-Roux et al., 2000), cancers (Maheswaran et al., 2006), mortality (Mackenbach et al., 1997; Hacking et al., 2011), self-reported health (Chandola et al., 2007; Cairns et al., 2012) and LLTI (Shouls et al., 1996; Harding and Balarajan, 2001; Boyle et al., 2002; Norman et al., 2005; Cairns et al., 2012),

Health inequality and *health inequity* are often used interchangeably, but there are differences that need to be recognised when conducting research into unequal health outcomes (Arcaya et al. 2015). Any measureable aspect of health that varies between population subgroups or places can be a health inequality (Shaw et al., 2007; WHO, 2013). In contrast, a health inequity implies that observed differences in health may be avoidable and unfair (Kawachi et al., 2002). Whilst health *inequalities* are uneven distributions of health across populations, health *inequities* are unjust inequalities produced as a result of societal arrangement rather than personal characteristics (Kawachi et al., 2002; Arcaya et al. 2015). Importantly, *inequities* require passing a moral judgment that the inequality is unfair (Arcaya et al. 2015). When

differences in health between groups are observed, a key consideration is whether the inequality in question is also inequitable (Pickett and Wilkinson, 2007).

2.3.1 The social gradient of health

The increasing prevalence of health conditions in line with poorer socioeconomic status is termed the ‘social gradient’ (Marmot, 2010). There is an extensive literature documenting pervasive and persistent socioeconomic gradients in health across the majority of health outcomes (Townsend et al., 1988; Benzeval et al., 1995; Acheson, 1998; Shaw et al., 1999; Kawachi et al., 2002; Davey Smith, 2002; Macintyre et al., 2005; Marmot, 2010; Benzeval et al., 2014). Those in the most socioeconomically advantaged positions have the best health outcomes, and those with the most deprived circumstances have the poorest (Benzeval et al., 2014). However, the association persists across the entire social spectrum (Benzeval et al., 2014; ONS, 2014a). On average, across the socioeconomic distribution, individuals will have poorer health than those above them and better health than individuals below them (hence the use of the term ‘gradient’). Since everyone below the very top suffers to some degree from unnecessary health inequality, tackling the social determinants of health inequalities will benefit everyone.

Exploring inequalities in life expectancy provides a useful illustration of the extent and unfairness of differences in health outcomes (Marmot, 2010). Figure 2.1 displays Life Expectancy (LE) at birth for males by decile of neighbourhood deprivation (one measure of socioeconomic disadvantage). People living in the most deprived areas in England have on average the lowest LE and conversely, LE is higher on average for those living in areas with lower levels of deprivation. Males living in the most deprived tenth of areas in England can expect to live nine fewer years compared with the least deprived tenth, and females can expect to live seven fewer years (ONS, 2018). The extent of health inequalities are more pronounced when considering Disability-free Life Expectancy (DFLE) (Figure 2.1). Individuals in the most deprived areas not only live shorter lives, but also spend a longer proportion of their lives in poor health and disability (ONS, 2018).

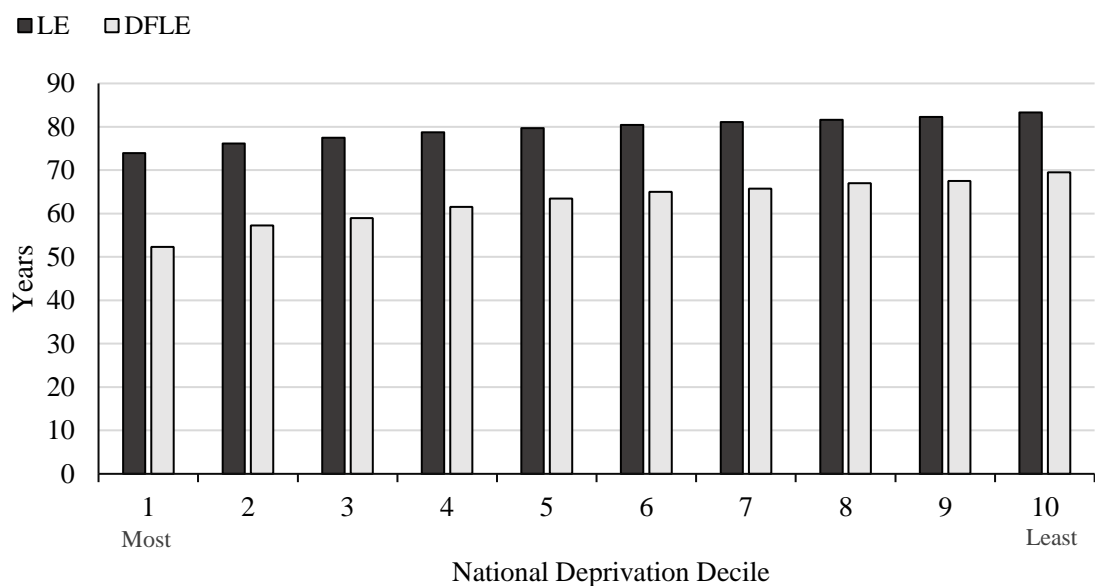


Figure 2.1: Life Expectancy (LE) and Disability-free Life Expectancy (DFLE) for males at birth by national deprivation deciles, England, 2015-2017

Author's calculations, data from (ONS, 2018)

2.4 Context versus composition: A useful distinction?

In recent years, researchers concerned with the connections between health and place have drawn on a wide selection of theoretical frameworks to examine how health is shaped in place and by place (Gatrell and Elliott, 2009). Health inequalities research has been dominated by a narrow and prevailing conceptualisation of place (Bambra et al., 2019) that has focused on distinguishing the relative importance of 'contextual' or 'compositional' explanations for area variations in health (Macintyre et al., 1993; Duncan et al., 1998; Smith and Easterlow, 2005).

Compositional explanations attribute geographical clustering of health outcomes to underlying individual demographic characteristics. Referring specifically to the age, sex, ethnicity and social class structure (Shaw et al., 2002), this explanation implies that people with similar characteristics will have similar health experiences regardless of the specifics of location (Senior et al., 2000; Sbrarra et al., 2011). Health is demonstrated to generally deteriorate with increased age (Marmot and Shipley, 1996; Chandola et al., 2007; ONS, 2014b). Variations by health outcomes between ethnic groups have also been observed across England (Darlington et al., 2015). Individuals with low-income are less likely to live in good quality housing, have good quality employment, afford healthy food and have time and money to participate in leisure activities (Joseph Rowntree Foundation [JRF], 2018). These socioeconomic inequalities in health determinants are not restricted to differences between the most privileged groups and the most disadvantaged; health inequalities exist across the entire

social gradient (Marmot, 2010). Individuals with similar personal characteristics often aggregate within geographical proximity, whether purposefully to share a common culture or because they are driven to certain areas because of their personal resources (Boyle et al., 2004; Smith and Easterlow, 2005). One of the mechanisms through which this ‘residential selection’ operates is through the ability to pay for housing, enabling some people to move into, and live, in certain areas whilst others are restricted by their financial resources (Macintyre et al., 1993). There is a significant body of work by health geographers on health selective migration and spatial sorting processes (Boyle et al., 2004; Tunstall et al., 2016) whereby poor health can lead to downward socio-spatial mobility. Under a compositional conceptualisation health patterns are merely reflective of differences in the underlying population structure of areas.

Collective social functioning and practices that are beneficial to health include high levels of social cohesion and social capital. Susser (1994) argues that the effects of aggregation in an area may mediate the effects on health of individual level variables, and stresses the significance of the effects of collective attributes of populations. The association between individual socioeconomic context and health might vary in relation to the aggregated socioeconomic profile of the population of which the individual forms a part. Individual ethnicity has been shown to relate to health differently when it constitutes a minority state from when it denotes membership of a majority group in the local population (Bécares et al., 2012). This broader interpretation of compositional effects suggests that ecological studies of health variation have potential to capture these unique effects of aggregation. Negative effects can result from area histories and reputations. For example, in areas with a history of racial oppression or where places are stigmatised on the basis of their reputation as especially deprived or otherwise undesirable, residents may be socially excluded and suffer additional health burden (Benzeval et al., 2014).

Contextual explanations suggest that ecological attributes of spatially defined areas such as the social, economic and physical environment affect the health of individuals exposed to them (Diez-Roux and Mair, 2010). Area variations in health are not simply reducible to the sociodemographic characteristics of residents, but reflect the broader social and spatial context (Macintyre and Ellaway, 2003; Smyth, 2008; Boyle et al., 2009; Andrews et al., 2014). This understanding would cause people with similar individual attributes to have different health experiences and outcomes from one area to another. Areas are a distinctive system of health relevant resources embedded within geographic borders (Curtis and Jones, 1998; Macintyre

et al., 1993). Area-socioeconomic factors that influence health are often summarised in terms of ‘area-level deprivation’.

Applying a contextual framework allows us to better understand why the health inequalities by neighbourhood deprivation observed in Figure 2.1 exist. Macintyre et al. (1993) found that residents similarly situated in terms of their personal circumstances had better health when residing in a less deprived areas. The social and physical environments in less deprived areas to be systematically better at promoting health of all residents regardless of personal circumstances (Macintyre et al., 1993). In the least deprived areas compared to the most deprived areas, Macintyre et al. (1993) found that healthy foodstuffs were available more widely and cheaper; there were more sporting and recreation facilities available locally; the local environment was less threatening; and, there was a more extensive primary health service. The assertion that the extent to which an area promotes health is directly relatable to its socioeconomic status has been further explored by The Department for Environment, Food and Rural Affairs (DEFRA) (2009). Analysis of selected environmental conditions including green space, litter and the presence of waste treatment sites revealed that 82% of the most deprived areas were found to experience one unfavourable environmental condition compared to 33% of the least deprived areas across the UK. Furthermore, 20% of the most deprived areas experienced four or more unfavourable conditions (DEFRA, 2009).

There is a common, but often implicit, view in much of the literature on environmental nutrition and physical activity that certain areas are self-evidently health promoting while others are self-evidently health damaging (Burns and Inglis, 2007; Macintyre et al., 2007). Mitchell and Popham (2008) demonstrate that mortality rates were lower in areas with greater levels of green space and that such associations were consistent in deprived areas. However, Macintyre (2007) argues that green space might be health-promoting for some individuals and health damaging for others and that dichotomising environmental resources as ‘goods’ and ‘bads’ is unduly naïve and simplistic. Similarly, the social meaning and symbolic significance of some resources have been shown to vary. Milligan and Bingley (2007) report that features such as woodland, which are often seen to be health promoting can be seen as ‘scary’ by some with potential implications for both physical and mental well-being. As demonstrated by Macintyre (2007), proximity to derelict land might seem threatening and a deterrent to joggers or elderly walkers, whilst simultaneously facilitating ball games and free play amongst children.

The narrow conceptualisation of place that has, until recently, dominated the health inequalities literature has significantly restricted and undervalued the importance of wider structural processes in shaping health inequalities (Bambra et al., 2019). Whilst the context-composition framing has been important in advancing understanding of the drivers of geographical inequalities in health, the pervasiveness of this approach has resulted in an incomplete account for why health is increasingly uneven across neighbourhoods, cities, regions and countries (Bambra et al., 2019). It is recognised that there is a mutually reinforcing and reciprocal relationship between people and place; a relational approach should therefore be taken to understand how compositional and contextual factors interact to produce geographical inequalities in health (Cummins et al., 2007; Riva et al., 2011; Bécarea et al., 2012).

Socioeconomic reality in a given geographical area is the product over time of larger scale, macro-political and socioeconomic factors (Bambra et al., 2019). As a result of residing in a particular area future life chances are shaped, most obviously through ability to find employment, but also through the provision of other opportunities both directly and indirectly related to health (Benzeval et al., 2014). An understanding of how these structural processes are entwined within the histories of places will help to explain inequalities. Although there are notable exceptions (Niedzwiedz et al., 2016), the general lack of attention amongst health geographers to structural drivers has resulted in conceptualisations that underrepresent the complex, multi-scalar and interdependent processes that operate over many decades to shape geographical inequalities in health (Bambra et al., 2019). This imbalance has important implications, not just in terms of understanding the causes of geographical inequalities in health but also for theorising and implementing appropriate, robust and sustainable policy solutions.

2.5 Wider determinants of health

The Marmot Review published in 2010 emphasised the strong and persistent links between political, social and economic factors and disparities in health outcomes. These determinants of health illustrate the societal processes and influences underlying the inequalities that determine health, including living and working conditions and the broader social structures in which they are embedded, as well as individual-level risk factors (Marmot, 2010). The conditions of daily life in which we are born, grow, live, work and age are influenced by the local, national and international distribution of power and resources (Dahlgren and Whitehead, 2007; Marmot, 2010). These wider factors determine the extent to which different individuals

have the physical, social and personal resources to identify and achieve goals, satisfy their needs, deal with changes to their circumstances and actively participate in life (Health Promotion International, 1986). Variation in the experience of wider determinants is considered the fundamental cause of unequal health outcomes (Dahlgren and Whitehead, 2007).

One framework which captures the interrelationships between wider socioeconomic and spatial determinants and health is the Dahlgren and Whitehead (1991) ‘Determinants Rainbow’ (Figure 2.2). This model provides a broad conceptual framework for considering the layers of influence on an individual’s potential for health, including; personal characteristics, lifestyle factors, social networks, living and working conditions, socioeconomic circumstances and environmental settings (Dahlgren and Whitehead, 2007). Represented at the centre of the model are core, non-modifiable factors including age, sex and genetics. This is surrounded by a set of potentially modifiable factors expressed as a series of layers of influence (Whitehead, 1995). Firstly, individual lifestyle and behaviours that can promote or damage health such as smoking habits and physical activity are represented. This layer is encircled by social and community level factors which influence health, and health behaviours, through social support, community interactions and societal norms and attitudes (Ball et al., 2010). This in turn is embedded within the wider structural factors; education, housing, employment and working conditions, and access to services (Dahlgren and Whitehead, 2007). This layer is enclosed within structural socioeconomic and environmental conditions and the wider global system including threats posed by bioterrorism, climate change and outbreaks of infectious disease (Dahlgren and Whitehead, 2007). The model also emphasizes interactions: individual lifestyles are embedded in social norms and networks, and in living and working conditions, which in turn are related to the wider socioeconomic and cultural environment (Dahlgren and Whitehead, 2007). Risk factors at an individual level are not independent of wider socioeconomic factors such as education, employment, community, culture and peer group influences. Strategies to impact on health inequalities as a whole need to include interventions addressing all levels (Whitehead, 1995).

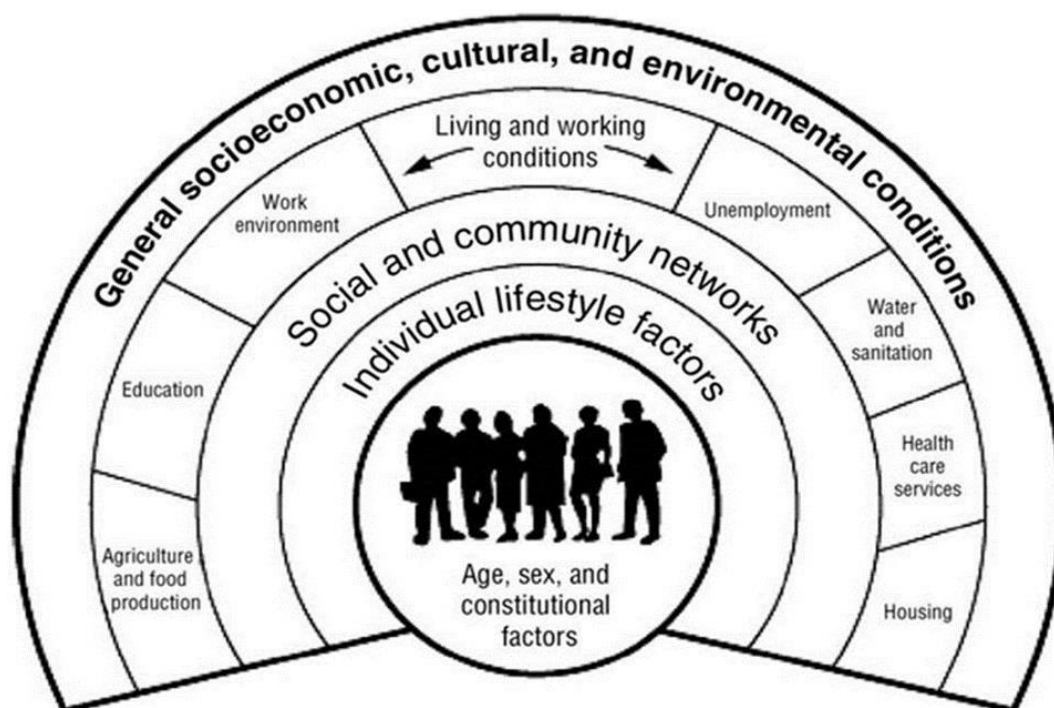


Figure 2.2: The 'Determinants Rainbow' model for understanding the determinants of health
Source: Dahlgren and Whitehead (1991)

It has been suggested that differences in risk factor prevalence are not the only reason for health inequalities (Hart, 1971; Downing et al., 2007; Dixon et al., 2007). Those areas which are deprived also experience additional disadvantages because of this deprivation, leading to double jeopardy effects (Macintyre, 2007). In 1971 Tudor Hart suggested the Inverse Care Law to describe how the availability of good medical care tends to vary inversely with the need for it in the population served (Hart, 1971). The Inverse Care Law has been shown in many different settings, including for cancer diagnosis (Downing et al., 2007), hip and knee replacements (Judge et al., 2010) and end of life care (Dixon et al., 2007). Downing et al. (2007) found significant socioeconomic inequalities in breast cancer survival and identified that these findings could be statistically explained by inequalities in receipt of treatment. Unwarranted variation in healthcare is therefore likely to disadvantage those in the most deprived areas or in certain groups, exacerbating health inequalities (Hart, 1971). Popay et al. (2003) in a comparison of the area characteristics of socioeconomically advantaged and disadvantaged areas in northern England found unequal distribution of health promoting services between more and less deprived areas; 8.6% of respondents in a socioeconomically deprived area reported good accessibility to a doctor's surgery, compared to 23.1% in a prosperous area. The evidence for such effects is contested within the literature. Macintyre et

al. (2008) find no significant differences for the location of General Practice (GP) Surgeries or Pharmacies across Glasgow.

2.6 The role of deprivation on health

Deprivation is widely thought of as a state of socioeconomic disadvantage relative to the local community, wider society or the nation to which an individual, family or group belongs (Townsend, 1987). Deprivation covers a broad range of issues and refers to unmet needs caused by a lack of resources of all kinds; both material infrastructure and collective social functioning may influence health (Townsend, 1987; Marmot, 2010). People can be deprived of adequate education, suitable housing, rewarding employment, sufficient income, and opportunities for social engagement (Dorling, 1996). Consequently, area deprivation is likely to be the cause of wide-ranging effects on health exerted through a myriad of material, behavioural, environmental and psychosocial pathways.

There is considerable evidence that area level socioeconomic deprivation has a damaging effect upon health (Diez-Roux and Mair, 2010; Bécaries et al., 2012) which has led to it being suggested to be the most important social determinant of health in high income countries (Benzeval et al., 2014). These findings are consistent whether deprivation is measured for individuals or based on the neighbourhoods where they live (Macintyre and Ellaway, 2003; Benzeval et al., 2014). Explanations for why neighbourhood deprivation might explain health inequalities includes deprivation shaping differential access to health relevant features and amenities (Macintyre et al., 1993; Popay et al., 2003; Cummins et al., 2007; Black, 2014; Livingston and Lee, 2014).

2.6.1 Measuring neighbourhood deprivation

The measurement of area deprivation has attracted considerable attention (Townsend, 1987; Carstairs and Morris, 1989; Martin et al., 2002). Quantifying the complexity of deprivation is a major challenge usually addressed through the use of composite indices that can reflect the multidimensional nature of deprivation better than any single variable such as income (Braveman et al., 2005). A wide variety of deprivation indexes have been devised which use several variables that each relate to different aspects of deprivation to provide a single summary score. Measures include Jarman Underprivileged Area Index (UPA) (Jarman, 1983), Townsend Index (Townsend, 1987), Carstairs Index (Carstairs and Morris, 1989), and the Index of Multiple Deprivation (IMD) (Department for Communities and Local Government, 2015). In Britain, measures have mainly covered relatively small area geographies and have

tended to make use of Census-derived variables so offer an insight into local socio-demographic conditions at a point in time (Senior, 2000).

The Townsend Index (Townsend, 1987) is a composite score comprising: unemployment, lack of access to a car or van, non-home ownership, and household overcrowding (more than one person per household room). Aiming to capture dimensions relating to material disadvantage, these measures are consistently available from Census data and match key aspects of material deprivation (Townsend, 1987). The Townsend Index has been widely utilised in academic studies and public health reports (Higgs et al., 1998; Norman et al., 2011; Lloyd et al., 2017b).

Deprivation scores are typically time point specific and scores from one period to the next are not directly comparable (Norman, 2010a). These inconsistencies and a lack of equivalent data over time make it difficult to study areas that have been amongst the consistently most deprived in absolute terms over time (Dorling et al., 2007; Whynes, 2008; Norman, 2010a). However, the increasing availability of administrative data at local levels has driven developments in the definition and measurement of deprivation (Dorling et al., 2007; Norman, 2010a; Exeter et al., 2011; Norman and Riva, 2012; Lloyd, 2014; Smith et al., 2015). Exeter et al. (2011) introduced a novel method for calculating Carstairs deprivation scores that could be compared over time using areas (Consistent Areas Through Time - CATT's) in Scotland whose boundaries remained stable over the period 1981-2001. This enabled a comparison of mortality rates for deprivation (im)mobility and demonstrated that the persistently most deprived areas in Scotland (1981-2002) had seen premature mortality rise by 9.5% during the two decades (Exeter et al., 2011). Norman (2010a) used the Townsend input variables to construct a time-series deprivation score. This facilitated the identification of change over time in small area socioeconomic deprivation. Measured in this way, deprivation was generally shown to have eased due to downward trends in levels of lack of access to a car, non-home ownership, household overcrowding but most particularly, to reductions in levels of unemployment (Norman, 2010a). Lloyd et al., (2017b) utilised the Townsend Index score to measure both relative and absolute deprivation change in Britain from 1971-2011.

2.7 Materialistic pathways of deprivation to health

Research aimed at understanding why neighbourhood deprivation might be a useful predictor of health patterns has explored the role that materialistic dimensions of deprivation have in producing divergent health trajectories of different places (Marmot, 2010; Benzeval et al., 2014; Jivraj et al., 2019). The material pathway relates to how (primarily) economic resources

and assets influence an individual's ability to engage in life (Dahlgren and Whitehead, 2007). Here several key dimensions of the material pathway are explained including their relevance to health.

2.7.1 Income

Income is often described as the most important economic factor relating to health (Benzeval et al., 2014; JFR, 2018). Income determines the availability of health-promoting goods and services, opportunities for social engagement and access to health promoting environments (MacInnes et al., 2013; Benzeval et al., 2014). A large body of research has demonstrated a consistent social gradient of health by income level (Benzeval et al., 2014; Cooper et al., 2015; JFR, 2018). For example, Cooper et al. (2015) find that with each £10,000 decline in income the duration of good health decreases by 30%. The importance of income not only relates to an individual's absolute level of resources, but also to the relative comparison of resources in wider society (Morris, 2010). As society becomes wealthier, the level of income considered adequate for a healthy life also increases (Morris, 2010). Structural determinants in the distribution of income throughout society also influence health patterns, with such patterns often observable through neighbourhood deprivation. Income inequality can lead to knock-on effects through notions such as 'deprivation amplification' whereby local contextual disadvantages are magnified when combined with the less adequate personal resources of those living in deprived areas (Macintyre, 2007). This structural inequality is shown to affect health through discrimination, dominance hierarchies, violence and underinvestment in human or social infrastructure (Berkman and Glass, 2000). It is recognised that the longer people live in stressful economic circumstances, the greater the physiological and psychological damage suffered (Jivraj et al., 2019). Despite its importance, information on income is not collected in the UK Census, and as such many measures of neighbourhood deprivation do not consider income within them (Rees et al., 2002; Norman, 2010b).

2.7.2 Employment

The literature has long acknowledged that employment status is a key determinant of health and health inequalities (Waddell and Burton, 2006; Schmitz, 2010; Belfield et al., 2014). Three main pathways concerning the link between unemployment and health are highlighted in the literature. Firstly, employees suffering from poor health are more likely to move towards unemployment (Benzeval et al., 2014) with adverse consequences more likely for those in lower socioeconomic groups (PHE, 2017). Data from the 2011 Census demonstrates that the divergence between the most and least deprived groups in terms of percentage with 'not good' health intensifies after ages 25 to 29, with the gap growing steadily across the working ages

of 30 to 64 when adults are expected to be valuable participants in the labour market (ONS, 2014a). In the same context, unemployed individuals with poor health are less likely to become employed; a relationship likely to be attenuated in areas with high unemployment rates (Bambra, 2010). Finally, the transition from employment to unemployment may be health damaging for healthy individuals (Ryan, 2000), especially if this occurs at sensitive periods of the life course (Jivraj et al., 2019).

Associations between employment and health have conventionally been explored through two inter-related concepts; material and psychosocial consequences. Employment is important for health as it provides financial resources which can be used to access essential health promoting goods, services and environments (Schmitz, 2010). The psychosocial benefits of employment include a sense of purpose and self-worth (Cooper et al., 2015), access to a more heterogeneous social network (Waddell and Burton, 2006), and the opportunity to participate positively in society (Poortinga, 2006). Consequently, unemployment not only effects health through associated financial hardship but can impact upon health outcomes through social isolation and loss of self-esteem (Shaw et al., 2002). The impact of unemployment on health is well-established even when social class and behavioural factors are controlled for (Riva et al., 2011).

Integrally linked to changes in the geographies of production and the emergence of new spatial divisions of labour, the nature of work has altered considerably in Britain in recent decades (Bambra and Garthwaithe, 2015). From the 1970s until the 1990s, increasingly competitive foreign markets and globalisation caused extensive industrial decline and regional restructuring in Britain (ONS, 2015a). This has produced concentrations of socioeconomic deprivation that have persisted over time with important implications for health (Hacking et al., 2011; Audureau et al., 2013; Webber et al., 2015). A number of formerly thriving industrial areas of Britain have undergone dramatic and rapid decline resulting in regionally concentrated falls in the demand for labour most notably in north west and north east England, and south Wales (Walsh et al., 2010; Riva et al., 2011). Over the same period the service industry in Britain has expanded considerably, employing 81% of England and Wales's working population in 2011 with many of these employment opportunities concentrated in London and south east England (ONS, 2015a).

Localised economic and social factors may act over time to amplify the effects of unemployment for poor health through underinvestment in human or social infrastructure and

services (Berkman and Glass, 2000). Deindustrialised regions are characterised by overall economic decline, environmental deterioration, social disruption (Riva et al., 2011) and limited labour market opportunities (Berkman and Glass, 2000). Higher outward migration of younger populations due to the lack of employment opportunities has also negatively impacted economic growth (Riva et al., 2011). Over time these conditions have produced socially and spatially isolated communities where the impacts of unemployment on health have been amplified. The literature has especially found coalfield related inequalities (Fitzpatrick et al., 2000; Riva et al., 2011; Norman et al., 2014). An investigation using data from the ONS Longitudinal study observed that overall mortality rates among men and women were significantly greater in coalfield areas than elsewhere in the UK (Fitzpatrick et al., 2000).

The quality and type of employment is an important consideration for unequal health outcomes. Labour market changes have been accompanied by a decline in the number of full-time and permanent roles and a rise in flexible, precarious employment with limited, or no, employment or welfare rights (MacInnes et al., 2013). The emergence of a twenty-four-hour society associated with the service industry and the increased use of shift work this entails has led to public health concerns about abnormal working patterns and work-life balance (Bambra, 2010). Growing evidence suggests that being employed does not necessarily alleviate economic and material disparities. Work does not provide a guaranteed route out of deprivation and many individuals are trapped in a cycle of low-paid, poor quality work (Benzeval et al., 2014). Individuals with no or few qualifications and skills, lone parents and those from some ethnic minority groups are more likely to be in low-paid, poor quality jobs with few opportunities for advancement, often working in conditions harmful to health (Belfield et al., 2014; ONS, 2015a). Skill mismatches that result in overall job dissatisfaction can be associated with negative health implications (Mactaggart et al., 2016), especially if the employment does not provide financial resources sufficient to relieve financial pressures (Cooper et al., 2015). A report by JRF (2018) suggests that in-work-poverty has been rising even faster than employment, driven almost entirely by increasing poverty among working parents. Of the 14.3 million people living in poverty in the UK, eight million live in families where at least one person works (JRF, 2018). Workers in four types of industry have particularly high rates of poverty: accommodation and food services (25%); agriculture, forestry and fishing (23%); administrative and support services (22%); and wholesale and retail (18%) (JRF, 2018). This compares with a poverty rate for workers overall of 13% (JRF, 2018).

2.7.3 Education

While the relationship between deprivation and educational attainment is recognised in the literature as co-associated, it is also complex with many dynamic dimensions (Boyle et al., 2009; Marmot, 2010). Geyer and Peter (2000) show that higher levels of literacy allow more educated individuals to make better-informed health-related decisions. Individuals with low educational attainment are more likely to be employed in stressful, unrewarding and depersonalising work with low-incomes, which have adverse effects for health (Marmot, 2010; Belfield et al., 2014). Higher educational attainment has been shown to correlate with obtaining secure and well-paid employment helping to reduce the negative impacts on health of disadvantaged living conditions from low income (Cooper et al., 2015). Although education in England is free of financial cost until age eighteen, continuing education beyond this can be expensive and is not pursued by all (Sparkes, 1999). Given the influence of social norms, children may have their education ambitions blunted if growing up in areas where poor educational attainment is normal, unemployment rates are high or good quality employment opportunities are scarce (Ball et al., 2010). Ineffective school-to-work transitions for those who do not attend university have been identified as a problem that is causing high youth unemployment (Ryan, 2000; Whitehead, 2014). Cooper et al. (2015) demonstrated that the burden of poor health increases with the duration of unemployment. Youth unemployment is thought to have particularly adverse long-term consequences for mental and physical health across the life course (Whitehead, 2014).

2.7.4 Housing

Housing is important for many aspects of healthy living and well-being. The home is the environment in which most people spend the majority of their time and is important for psychosocial reasons (Gibson et al., 2011). There is evidence that people living in deprived neighbourhoods suffer from a poorer quality of housing (Smith, 2012; Ward, 2015).

Housing quality acts as a mechanism through which socioeconomic inequalities can produce health disparities (Macintyre and Ellaway, 2003). It has been demonstrated that living in cold and damp conditions increases the risk of contracting respiratory infections, chronic illnesses and mental health problems (Poortinga, 2006). A further aspect of housing quality is the quantity of housing that is available to each member of a household. A household is classified as overcrowded if it has at least one bedroom too few for the number and composition of people living there (ONS, 2015b). Crowded housing conditions can create stress in the home and have negative health consequences for inhabitants (Shelter, 2005). Residents living in overcrowded households reported significantly higher levels of poor health compared with

those living in under-occupied households (ONS, 2015b). The quality of privately rented housing, specifically of Houses in Multiple Occupation (HMO) has been highlighted as key in the development of geographical health inequalities (Simmonds, 2009). The HMO landscape created through the decline of large hotels, houses and guesthouses has resulted in coastal areas having disproportionality high levels of poor-quality housing (Depledge et al., 2017). This has created a buoyant private rental market for low-income, often vulnerable groups (Ward, 2015) driven to coastal areas through the availability of housing and the willingness of landlords to accept Housing Benefit (Beatty and Fothergill, 2004). As demonstrated by Ward (2015) after relocating to a seaside HMO accommodation residents often find it difficult to find employment opportunities due to the nature of coastal area development, low-skilled seasonal work and isolation from larger centres of employment.

The distribution of people across residential areas is neither inadvertent, nor entirely intentional (Macintyre and Ellaway, 2003). Residential location is shaped by a number of factors including economic resources, service availability, environmental quality and social connections (Macintyre and Ellaway, 2003; Anselin et al., 2006). Individuals with similar personal characteristics often aggregate within geographical proximity whether purposefully to share a common culture or because they are driven to certain areas because of their personal resources (Boyle et al., 2004; Smith and Easterlow, 2005). Smith and Easterlow (2005) argue that health experiences are systematically and unequally mapped onto housing outcomes. One of the mechanisms through which this ‘residential selection’ operates is the ability to pay for housing, enabling some people to move into, and live, in certain areas whilst others are restricted by their financial resources (Macintyre et al., 1993). Poor health can have a negative impact on an individual’s ability to meet housing costs, and can directly influence housing choice (Benzeval et al., 2014). As a result, individuals suffering from poor health may be selectively drawn into health damaging environments or at risk of displacement, or exclusion, from health promoting localities (Smith and Easterlow, 2005). It has been suggested that some neighbourhoods have healthy profiles because they exclude or eject ‘unhealthy’ people (Smith and Easterlow, 2005).

2.7.5 Psychosocial pathways

Deprivation also relates to the quality of the surrounding social environment (Mackenbach and Howden-Chapman, 2003; Smith et al., 2014). Health is affected by more than the physical characteristics of the places in which people reside, and poor health may be influenced by social context as well as how individuals feel about, identify with and act in their place of

residence (Smyth, 2008). The literature on the social environment and health considers numerous dimensions including personal relationships (Wilson and Oswald, 2005; Sbarra 2015), community norms and attitudes (Ball et al., 2010), social support (Kawachi and Berkman, 2000; Smyth, 2008), social capital (Keene et al., 2013), collective functioning (Livingston and Lee, 2014), and power and hierarchy (Rosenberg, 2014).

Local areas have stressors that can affect health negatively (Macintyre et al., 1993). At the same time these areas can provide resources to help mitigate the health risks of these stressors, often this is in the form of social capital (Kawachi and Berkman, 2000). Societies that have a more equal distribution of income are also those which are more cohesive and where levels of trust, reciprocity, cooperation and civil engagement are higher (Wilkinson and Pickett, 2006). Smith et al. (2014) when comparing reported self-rated general health among adolescents in different east London boroughs, found a consistent association between positive social environments and better health. Social support networks facilitate the diffusion of health advice, as well as providing emotional and practical aid (Kawachi and Berkman, 2000). Poortinga (2006) suggests that affluent individuals have wider, heterogeneous social networks which offer advantages for health in terms of diffusion of influence, information and opportunities for social mobility. Social support and integration may have a greater impact in poorer areas, as these individuals are more likely to be geographically restricted to the immediate local area (Kawachi and Berkman, 2000). Despite this, social networks in deprived communities have been characterised as socially homogenous and may be isolated from the diffusion of health-related information (Pickett and Pearl, 2001; Smith et al., 2014).

Most discussion of social capital had considered it to be a positive asset for a society to have, however, inequalities that exist in the distribution of income, employment, skills, education and housing are systematically associated with social disadvantage and marginalisation (Macintyre, 2007; Marmot, 2010; WHO, 2010). Areas vary in the extent to which they induce stress or provide social support (Rosenburg, 2014). The differences impact upon the health of all people living in the area, regardless of their individual socio-economic circumstances (Pickett and Pearl, 2001). Portes (1998) cautioned that social capital can lead to negative outcomes including exclusion of outsiders, restriction on individual freedoms and downward levelling norms. The systematic unequal distribution of power, prestige and resources among groups in society operate to exclude certain groups from health-promoting opportunities (Rosenburg, 2014). People can be excluded from the consumption of health promoting goods, services, environments and chances of social and democratic participation in health policy that

can contribute positively to health and well-being (Smith and Easterlow, 2005; Rosenberg, 2014).

Wilson's (1987) social isolation theory argues that neighbourhoods of concentrated deprivation can become socially isolated from other areas and wider society. Where deprived places are stigmatised and socially segregated, undesirable localised cultures can emerge. Wilson's theory focused on Chicago, evidencing the impact of local communities from long-term economic decline brought about by falling manufacturing job opportunities in inner city areas (Wilson, 1987). With fewer job opportunities (especially due to employers locating outside of urban centres on cheaper land) and skills mismatch of local populations unable to take advantages of growing high skill service sector employment opportunities, deprivation levels became increasingly concentrated in areas both socially and spatial isolated (Wilson, 1987). Social and cultural norms changed as a result of being isolated and unhealthy behaviours including excessive alcohol consumption, smoking, unsafe sex, drug misuse, poor diet and low rates of physical activity became more socially acceptable (Wilson, 1987; Berkman and Glass, 2000). Benzeval et al. (2014) suggest that the difficulties of everyday life that can be caused by residing in a deprived area can result in people heavily disregarding the future. As a result they are less concerned with the health damaging effects of behaviours that bring them current stress relief (Benzeval et al., 2014). Wilson's theory demonstrates how the psychosocial and material pathways interact together to impact health (Wilson, 1987).

2.8 Demographic mobility, deprivation and health

Contextual material resources and opportunity structures are linked and modified by personal characteristics including age, gender, ethnicity and country of birth (Macintyre, 2007; Harris et al., 2006; Diez Roux and Mair, 2010). Often these are treated only as personal attributes obscuring the structures of (dis)advantage and discrimination that make them important influences on health (Graham, 2000). Changing deprivation circumstances can be both a cause and a consequence of demographic change and the literature documents several reinforcing mechanisms through which the wider determinants of neighbourhood physical and social environments contribute to changing health inequalities (Macintyre and Ellaway, 2003; Boyle et al., 2004; Cummins et al., 2007; Bécares et al., 2012). Individuals may have characteristics that make them more vulnerable to adverse contextual conditions, while others may have the personal and financial resources that allow them to overcome deficiencies or hazards in their area (Diez Roux and Mair, 2010).

2.8.1 Age

Age is a key risk factor in the development of poor health, with well-established associations between older age and poorer health outcomes (Marmot and Shipley, 1996; Chandola et al., 2007; ONS, 2014a). The age structure of the population is determined by past and current fertility and mortality trends, as well as migration patterns (Poston and Bouiver, 2010). The population of Britain is ageing, a trend that is expected to continue, with increasing life expectancy contributing to the fastest population increases in those aged 85 and over (ONS, 2012). By 2035 it is projected that those aged 65 and over will account for 23 percent of the total population and the number of people aged 85 and over will be almost 2.5 times larger than in 2010, reaching 3.5 million and accounting for five percent of the total UK population (ONS, 2012). This presents societies with new challenges in terms of health and wellbeing, including caring for increasing numbers of people with long-term conditions (McCracken and Phillips, 2012).

Two thirds of the population with a LLTI or disability are aged 55 and over (ONS, 2014a). The effects of old age on health are not equally distributed throughout the population; socioeconomic status, gender and ethnicity have as much influence on health status in old age as they do in other life stages (McCracken and Phillips, 2012; Sabater et al., 2017). Ethnic minorities over 65 are more likely to experience deprivation than the majority population, with detrimental effects for health documented (PHE, 2017). Whilst absolute differences in health outcomes between socioeconomic groups increases at older ages (Marmot and Shipley, 1996), evidence on relative health inequalities among older people is conflicting. Some studies show converging relative health inequalities among the oldest age groups that may result from period effects such as retirement (Huisman et al., 2003; Von Dem et al., 2003). Others find persisting or even widening inequalities in health later in life. Chandola et al. (2007) show that social inequalities in self-reported health increase in early old age; people from lower occupational grades age faster in terms of a quicker deterioration in physical health compared with people from higher grades.

Age is an important mechanism of residential location and, through propensity to move, spatial sorting of populations. Sabater et al.'s (2017) research from England and Wales demonstrates increased spatial separation between older (65+) and younger (25-40) age groups over the last 20 years. This work identifies a pattern of reduced geographical spread over time of older compared to younger adults across neighbourhoods in northern cities and suggests an important socioeconomic dimension to age segregation (Sabater et al., 2017). Recent evidence

from the UK suggests that residential mobility has decreased among adults aged 65 and over since the 1970s (Vanderbeck, 2007; Champion and Shuttleworth 2016), and evidence from Scotland indicates that this has been particularly pronounced in recent years (Graham et al., 2015). The recent housing market crisis has resulted in reduced mobility among younger people contributing to pronounced ‘youthification’ of cities and resulting age segregation processes (Vanderbeck, 2007; Vanderbeck and Worth, 2014; Moos, 2016).

In recent decades older people generally are wealthier and living longer than previous generations (Age UK, 2015). In the short-term this may facilitate migration for retirement, a process which may result in an increased concentration of elderly people in certain areas who are likely to develop a LLTI as they age (Sabater et al., 2017). Migration among older groups is generally divided into that which is voluntary and that which is constrained by personal circumstances, including health (Champion, 2012). Voluntary migration is generally undertaken by those who are recently retired, usually relatively affluent and healthy, who seek a move for reasons of amenity and leisure (Sander and Bell, 2013). The second group often comprises older migrants who are less able to care for themselves, or who anticipate a need for care (McCracken and Phillips, 2012). This group includes those moving to be nearer children and other relatives, perhaps after losing a partner, as well as those who develop a disability or chronic illness that necessitates institutionalised care (McCracken and Phillips, 2012).

2.8.2 Ethnicity

Studies have demonstrated that some ethnic groups disproportionately suffer from specific poor health outcomes. For example, Gujral et al. (2013) found heightened insulin resistance among South Asians compared to Whites resulting in higher rates of Type 2 diabetes among South Asian groups. Hussain et al. (2013) demonstrated higher incidence of cardiovascular disease risk amongst South Asians, with changes in lifestyle following migration to western countries hypothesised to explain this (Hussain et al., 2013; Gujral et al., 2013). Others have argued that differences in culturally influenced lifestyle choices are not sufficient to adequately explain susceptibility to specific morbidities or overall ethnic differences in health (Nazroo, 2001; Kaufman et al., 2015; Darlington et al., 2015). Rather than resulting from biological or cultural features inherent in different ethnic groups, it is reasoned that widening ethnic inequalities in health are associated with differences relating to socioeconomic and broad spatial inequalities (Darlington et al., 2015).

The socioeconomic determinants of health are unequally distributed across ethnic groups, leading to unjust and preventable health inequalities (Nazroo et al., 2007; Jivraj and Khan, 2015). Different minority ethnic groups are disproportionality distributed across the social classes and between area types and demonstrated to concentrate in more disadvantaged circumstances (Modood et al., 1997; Nazroo, 1998; Barnard and Turner, 2011) characterised by lower incomes (Hills et al., 2010; Nandi and Platt, 2010), poor quality housing or temporary tenancies (Smith, 2012; Ward, 2015), inequalities in education (Gillborn, 2008) and poorer employment opportunities (Catney and Sabater 2015; Lymperopoulou and Finney, 2016). These disadvantaged circumstances are all associated with poorer health (Marmot et al., 1991; Marmot, 2010; Gibson et al., 2011; Darlington et al., 2015).

The marginalisation of ethnic minority groups in society is a form of racial discrimination (Gillborn, 2008; Black, 2014). Racism jeopardises health directly, and indirectly through compounding experiences of disadvantage (Karlsen et al., 2002; Harris et al., 2006). The stressors of racial harassment or discrimination are associated with adverse mental health (Krieger et al., 2005) and poor self-assessed general health (Karlsen and Nazroo, 2002). Whilst ethnicity may not be directly relevant to health, it is relevant to experiences of the wider determinants of health (Darlington et al., 2015).

Research has also explored the extent to which concentrations of ethnic, cultural and religious groups may protect against harmful characteristics associated with increasing deprivation (Karlsen et al., 2002; Pickett and Wilkinson, 2008; Bécaries et al., 2009). Discussions around the ethnic density effect propose positive health outcomes for residents living in areas with higher concentrations of their own ethnic group (Platt, 2007; Bécaries et al., 2009). Protective effects include enhanced social cohesion, improved social support, provision of cultural specific services not available elsewhere, and a sense of belonging (Hutchinson et al., 2009; Das-Munshi et al. 2010). These buffering effects provide protection from the adverse consequences of discrimination and racial harassment, as well as from the detrimental effects of low status stigma (Platt, 2007).

Ethnic density effects are contested and the pathways by which they operate are poorly understood (Bécaries et al., 2012). In some research findings, particularly in the United States (US) an 'ethnic density effect' has been demonstrated to offset the impact of area and individual level deprivation on health outcomes (Pickett and Wilkinson, 2008). This has been found for several health outcomes including adult mental health (Cairns, 1988; Halpern, 1993)

and birth weight (Pickett et al., 2009) among some minority ethnic groups in urban areas (Pickett and Wilkinson, 2008). The association between ethnic density and health appears more variable in studies conducted in the UK. A protective effect on health has also been demonstrated when individuals perceived greater own ethnic density in their area (Stafford et al., 2009). Bécaries (2009) found that ethnic minority people were not found to report higher civil engagement as ethnic density increased, but they were found to be more satisfied with local services and to report greater community cohesion. Hutchinson et al. (2009) established a stronger ethnic density effect in neighbourhoods with high social capital. In contrast, Lymperopoulou and Finney (2016) argue that the negative effects of area deprivation often conceal any potential ethnic density benefits associated with residing in areas with a higher concentration of ethnic minority people. Pickett and Wilkinson (2008) found that members of ethnic minorities who live in areas where there are few other ethnic minority individuals are likely to be residing in less deprived neighbourhoods compared to those who live in areas with a higher concentration of ethnic minority people. However, through the eyes of the majority community they may be more aware of belonging to a 'low status' minority group and this stigma may override any material advantage (Pickett and Wilkinson, 2008). London is the most ethnically diverse region of Britain and, combined with its socioeconomic profile, has a unique a pattern of ethnic health inequalities compared to other regions (PHE, 2018). Ethnic health and employment inequalities in London are more severe than elsewhere (Lymperopoulou and Finney; 2016). For example, Bangladeshi women in London were found to be more than 30% more likely to have an LLTI than White British women in London, compared to 15% more likely outside of London (PHE, 2018).

Ethnic density effects may be greater for recent migrants, and there may be changes according to length of residence (Kearns et al., 2017). The Healthy Immigrant Effect (HIE) posits that recent migrants are in better health than the host population and other migrants who have lived in the host country for a long time (Domnich et al., 2012). Migrants differ from the general population in terms of a number of factors including stage in life course, age, marital status, tenure and ethnicity (Champion and Ford, 1998). Such differences in turn change and deteriorate over time as migrants adopt health behaviours characteristics of receiving populations (Kearns et al., 2017).

2.8.3 Migration

Migration is a key mechanism between personal characteristics and health profiles (Boyle and Norman, 2010a; Green et al., 2015). Migrants are not a random subset of the population, the

social and demographic characteristics of migrants are different from those of non-movers (Boyle and Norman, 2010). Population subgroups such as the young (Boyle et al., 2004), highly qualified (Dorling and Thomas, 2004) or affluent are more likely to migrate (Catney and Simpson, 2010; Champion, 2012). Migration is an important process that, through the sorting of individuals in terms of their health, contributes to growing polarisation and inequality in health patterning (Boyle and Norman, 2010).

The literature has examined ‘health selective’ residential migration whereby migration acts as an internal sorting process (Boyle and Norman, 2010; Green et al., 2015). Health selective migration patterns play a significant role in determining the spatial distribution of health inequalities (Green et al., 2015). As differently healthy groups transition between areas or social classes, this sorting process may maintain, widen or constrain existing health gradients (Boyle and Norman, 2010; Darlington-Pollock et al., 2017). Social determinants of health or contextual influences will simultaneously maintain or exacerbate existing health gradients (Darlington-Pollock et al., 2017). Thus, those in the best health remain in (or transition between) the most advantaged circumstances whereas those in the poorest health remain in (or transition between) the least advantaged circumstances (Darlington-Pollock et al., 2017). Darlington-Pollock et al. (2017) suggest that the concept of selective sorting encapsulates three distinct mobility processes: social mobility relating to changes in social status through occupational change, residential mobility or migration, and deprivation mobility linked to changes in the socioeconomic characteristics of an individual’s residential area, whether or not they move. Norman et al. (2005) note that the effect selective migration has on health inequalities is reinforced by a significant group of people in poor health from less deprived areas moving to more deprived locations (Norman et al., 2005). Green et al. (2015) explored the association between migration by area type and health, finding evidence that individuals of poorer health were more likely to migrate to areas with poorer mortality profiles, and associated poorer social characteristics. These patterns are noted in other work but there are variations of findings in relation to geographic scale (Brown and Leyland, 2009) and the time frame of studies (Boyle et al., 2002; Riva et al., 2011).

The selective migration of healthy individuals from deprived areas to areas with better health profiles has been shown to play a significant role in determining location-specific health and mortality rates (Boyle et al., 2002; Norman et al., 2005). Importantly, recognising the inter-dependence of migration and deprivation mobility in terms of the relationship with (changing) health gradients introduces the idea of residualised populations. Smith and Easterlow (2005)

suggest that neighbourhoods are becoming increasingly similar whilst neighbouring areas are ever more divergent fundamentally because housing systems work to exclude or ‘trap’ individuals based on their personal circumstances. Norman et al. (2005) demonstrated that between 1971 and 1991 the largest absolute flow of people within England and Wales was that of healthy individuals moving from more deprived to less deprived areas. The impact of such movement was found to raise poor health in the deprived ‘origin’ areas, creating residual polarisation and contributing to widening spatial health inequalities observed across England and Wales (Norman et al., 2005). In a study of place-based health inequalities in northern England Popay et al. (2003) found that 66.4% of individuals residing in socioeconomically disadvantaged areas felt ‘dissatisfied, unhappy, or terrible’ about living in that locality, with 79.3% of residents wanting to move away from the area but unable achieve this. However, it is important to note that not all residents of deprived areas are socioeconomically deprived, and conversely, not all deprived individuals reside in deprived areas (Shaw et al., 2002).

There is a significant body of work by health geographers on health selective migration and spatial sorting processes (Boyle et al., 2004; Tunstall et al., 2016). Differently advantaged people move in different ways (Green et al., 2015). There are also differences in propensity to move based on health which is in turn influenced by age, ethnicity and socioeconomic status (Boyle et al., 2004; Tunstall et al., 2016; Darlington-Pollock et al., 2017). Further, health may be influenced by, but also influence, social and geographic mobility, linking contextual and compositional influences on health through the changing experience of place and social status (Boyle and Norman, 2010; Darlington-Pollock et al., 2017). The link between deprivation and health is often based upon comparison of the deprivation in a person’s residential area at the time that a particular illness was identified or death occurred (Davey Smith et al., 1997). However, the health status of individuals may reflect previous places of residence rather than the present one (Davey Smith et al., 1997). Indeed, older people are more likely to migrate if they are ill than if they are well (Bentham, 1988). Younger migrants are generally healthier than non-migrants and as a result, illness and mortality rates will fall in places that are gaining these people (Boyle et al., 2001; Exeter et al., 2005) and rise in places that are losing these people. Alternatively, selective migration could lead to an increase in illness and mortality rates of both the origin and destination if the migrant has better health than average in the place they are leaving but worse health than the place they are joining (Boyle et al., 2001). Furthermore, some people may experience different levels of deprivation during their life course without migrating (Boyle et al., 2004). Various initiatives across the Britain including neighbourhood renewal and area regeneration schemes are designed to improve the relative

conditions of places with the expectation that this will benefit the health and wellbeing of the people who reside there (Boyle et al., 2004).

2.9 A Geographical perspective

Measures of health status such as life expectancy are shown to be more favourable in some geographical locations than others (ONS, 2018). Geographic inequalities in health are well documented in Britain with differences in health found between the north and south (Whitehead, 2014), urban and rural communities (Lankila et al., 2012), between deprived and more affluent areas (Livingston and Lee, 2014) and by area type (Ward et al., 2015). Inequalities are found to be strongly patterned in relation to factors such as income, environment, housing quality, unemployment, access to services and education (Pickett and Pearl, 2001; Macintyre et al., 2005; Diez-Roux and Mair, 2010; Putrik et al., 2015). When researching health and deprivation, a geographical perspective is therefore paramount. Ignoring the role of geography serves only to restrict any understanding of patterns and processes necessary to tackle inequalities (Harris et al., 2005). Understanding how a population is unequally distributed between residential locales, and how these experiences of inequality manifest themselves in health, is a central theme in population studies. Understanding inequalities not only at a single point in time but also across generations in a community or geographical location is key to illuminating the processes through which spatial inequalities are being maintained and how they might be successfully reversed (Pearce, 2015).

Over the last two decades, the emergence of the field of Health Geography has been successful in re-establishing interest in the role of place in shaping health and health inequalities (Kearns and Moon, 2002; Macintyre and Ellaway, 2003). Influenced by studies such as the Black Report (DHSS, 1980), the 1990s saw an evolutionary shift away from a strictly biomedical model of understanding health where ‘place’ was simply a manner of displaying information, towards place being incorporated in analytical understandings of health (Kearns, 1993). Reflecting this shift, the name for this research interest changed from ‘Medical Geography’ to the ‘Health Geography’ (Kearns and Moon, 2002). Places are dynamic spatio-temporal products that operate within complex networks that are affected by, and affect wider structural processes (Massey, 2005; Riva et al., 2011). Health Geography recognises that the relations between health and place have to be understood as a set of interrelated processes operating simultaneously at various spatial and temporal scales (Riva et al., 2011; Lekkas et al., 2017; Pearce et al., 2018).

Research has made progress in detecting and understanding place effects on health (Popay et al., 2003; Cummins et al., 2007; Diez-Roux and Mair, 2010; Zhang et al., 2011), as well as documenting large disparities in premature mortality and morbidity at a range of spatial scales (Griffiths and Fitzpatrick, 2001; Davey Smith et al., 2002). Few analyses have been conducted for the whole of Britain; those that have, have used larger geographical units contributing to a reduction in the geographical detail obtained. Using data at a county level across Britain, Senior (1998) investigated variations in LLTI and found large under-predictions of LLTI in Welsh localities. At a somewhat more refined geographic scale, Dutey-Magni and Moon (2016) explored the spatial structure of chronic morbidity across Local Authority Districts (LADs) and middle-layer super output areas (MSOAs) finding patterns of spatial dependency in the geographical distribution of LLTI. Much work has focussed on comparative studies in contrasting socioeconomic areas (Macintyre et al., 1993; Popay et al., 2003), documenting the complex extent to which different social, cultural and economic environments undermine or enhance an area's health profile (Macintyre et al., 1993; Pickett and Pearl, 2001; Macintyre et al., 2005; Poortinga, 2006; Diez-Roux and Mair, 2010; Livingston and Lee, 2014; Putrik et al., 2015). To date, studies have encompassed a range of individual and area level data associated with health outcomes, but have largely been based on the assumption that the relationship between contextual factors and health is spatially homogenous.

Evidence of the importance of geography can be viewed through the unique and diverse health experiences of populations in different area typologies across Britain. Chilvers (1978) suggested that mortality steadily increases with levels of urbanisation. Kyte and Wells (2010) demonstrated that overall life expectancy was consistently higher in rural compared to urban locations. However, this rural advantage is argued to vary between population subgroups (O'Reilly et al.; 2007). O'Reilly et al. (2007), for example, observed that the protective effect of rurality fails to extend into older ages, adding that mortality tends to converge at older age groups. There is also a need to engage more critically with localities beyond urban-rural binaries (Ward et al., 2015). As demonstrated by Ward (2015) coastal areas face problems associated with both rural and urban areas. Rural parallels include isolation from the labour market and remoteness, whilst the quality of privately rented housing and deindustrialisation faced by these areas are traditionally more 'urban' concerns.

A 2017 report by the Social Market Foundation (SMF), which compared earnings, employment, education and health data in Local Authority areas, identified pockets of significant deprivation in seaside towns, and a widening gap between coastal and non-coastal

communities (Corfe, 2017). The long-term decline of core industries has been identified as important to the profound health and wellbeing challenges experienced in coastal towns (Corfe, 2017). This includes the decline of domestic tourism, but also fishing, ship building and port activities (Depledge et al., 2017). This has resulted in a relatively narrow industrial base in coastal areas contributing to insecure, low paid and seasonal employment and skills gaps (Depledge et al., 2017). Coastal localities tend to be characterised by an ageing population of long-term residents or incoming retirees with a transient younger, but marginalised group (ONS, 2014b). A House of Lords Select Committee Report '*Regenerating Seaside Towns and Communities*' (2019) found a low number of doctors per head of population, perpetuating the Inverse Care Law in such areas (Hart, 1971).

Evidence has also demonstrated coalfield related inequalities (Norman et al., 2014). Fitzpatrick et al. (2000), using data from the ONS Longitudinal study, observed that overall mortality rates among men and women were significantly higher in coalfield areas. These elevated mortality rates are not explained merely by concentrated levels of deprivation that have persisted over long periods of time (Hacking et al., 2011; Audureau et al., 2013; Webber et al., 2015). In addition to the direct physical effects associated with working in the coal mining industry, coalfield populations have faced deindustrialisation and associated unemployment, social and economic decline (Walsh et al., 2010). This overall economic decline, environmental degradation and social disruption has been pinpointed as a possible source of influence over health outcomes for the entire population of a deindustrialised areas (Taulbut et al., 2014).

The spatial arrangement of area characteristics has implications for health outcomes (Caughy et al., 2007; Sridharan et al., 2007). Deprivation in proximate neighbourhoods has been shown to have a negative influence on health outcomes in the neighbourhood of study (Graham et al., 2000; Boyle et al., 2001). Sridharan et al. (2007) using Scottish data found that mortality in postcode sectors was significantly higher in those sectors which had high levels of deprivation in the proximate sectors. This investigation highlights that spatial patterns of deprivation, rather than just levels of deprivation, might be implicated in explaining variations in health (Sridharan et al., 2007). Cox et al. (2007) found that poorer neighbourhoods which were surrounded by more affluent neighbourhoods had lower levels of Type 2 diabetes compared with other deprived neighbourhoods, and conversely, that affluent neighbourhoods surrounded by more deprived neighbourhoods had higher than expected rates of Type 2 diabetes. Using all-cause mortality in north west England, Zhang et al. (2011) examined the

impact of deprivation inequality on mortality. This research demonstrates a positive linear effect of the differences between the levels of deprivation in a neighbourhood and its surrounding neighbourhoods; when differences are high between the neighbourhood and surrounding areas there is a negative impact on mortality in that neighbourhood (Zhang et al., 2011).

Comparative analysis has shown that patterning of health and deprivation are deeply entrenched, such that historical distributions of deprivation are demonstrated to be strong predictors of contemporary health patterning (Dorling et al., 2000; Gregory, 2009). Dorling et al. (2000) compared the spatial arrangement of deprivation finding that the spatial distribution of poverty in inner London was relatively similar in 1896 and 1991; deprived places were found to remain relatively deprived, and more affluent localities remained affluent (Dorling et al., 2000). A study of England and Wales using standardised mortality ratios and period-comparable measures of deprivation found that areas with the highest levels of deprivation in 1900 continued to have high levels in 2001 (Gregory, 2009). After adjusting for contemporary deprivation, a significant correlation between standardised mortality ratios from both periods remained (Gregory, 2009).

2.10 Methodological considerations of geographical approaches

To fully explore spatial influences upon health robust spatial analytical methods and data available at appropriate scales are required.

2.10.1 Techniques

Underpinning geographic thinking is the assumption that spatial phenomena vary across a landscape (Tobler, 1970; Anselin, 1996). Space is continuous and neighbouring geographies are likely to share similar compositional and contextual characteristics that are spatially correlated. “Everything is related to everything else but near things are more related than distant things” (Tobler, 1970, p.236). More specifically, a set of conditions in one area may affect health outcomes in neighbouring areas (Tobler, 1970). Yet much geographically-focused health inequalities research to date has relied on conventional non-spatial methodologies. Ignoring the spatial dependencies between variables may result in biased estimates, misleading conclusions and consequently, ineffective interventions (Anselin, 1996).

Global techniques model space as a discrete entity rather than a continuous parameter (Lloyd, 2010), and do not account for the fact that place level factors can be interconnected. It is important to examine health patterns with measures that account for spatial variation and do not assume space to be constant or inactive over the study area. Non-stationarity is a common phenomenon in any geographical-based research (Pearce et al., 2018). The rising popularity of new methodological advancements such as multilevel regression has stimulated empirical research and considerations of theory, all of which increase the legitimacy of the geographical approach (Dorling, 2012). This has been aided through greater availability of low level, detailed data sources and a growth in computing power that allows spatial elements to be incorporated into modelling.

Geographic Information Systems (GIS) can be used to manage and retrieve geo-referenced data, demonstrating value in facilitating the spatial linking of diverse health, social and environmental data. Further, the visualisation of spatial relationships possible through GIS has made a valuable contribution to spatial inequalities research (Bindu & Janak, 2012). Using GIS, Dorling et al. (2000) were able to establish that health inequalities in London remained embedded over time, highlighting the strong and complex relationship between spatial patterns of health and local environmental characteristics. Over the last two decades a local-based regression technique, Geographically Weighted Regression (GWR) has gained popularity for exploring spatial non-stationarity among data. GWR techniques are under-utilised throughout the literature and to date few studies have employed GWR to examine contextual influences on health outcomes. Notable exceptions include the obesity literature (Black, 2014) as well as health outcome research in the US and Canada (Bagheri et al. 2009). Bagheri et al. (2009) used GWR to explore location variation in travel time accessibility to primary healthcare in Canada, establishing that areas with the highest travel time were also those with high deprivation scores (Bagheri et al., 2009). Black (2014) employed GWR to explore non-stationarity in the relationship between obesity and selected covariates in the US, establishing that place matters for health in terms of obesity prevalence, as the relationship between obesity prevalence and ecological influences varies substantially across place at the county-level. Clary et al. (2016) utilised GWR in a UK context to explore associations between the residential food environment and fruit and vegetable intake in London.

2.10.2 Geographical units

Aggregated data for populations of geographical areas have been widely used to examine social and economic differences in health, especially in studies of mortality (Hacking et al.,

2011). When using aggregated measures individual deprivation can potentially remain hidden as the aggregate measure is a simple sum of the individuals in an arbitrary area. This formal misconception in the interpretation of statistical data is known as the ecological fallacy (Lloyd, 2010). Characteristics of aggregated population's might be used to generate inaccurate assumptions about individuals within that population (Curtis and Rees Jones, 1998). For example, Townsend (1979) argues deprived areas will include many people who are not deprived, whilst overlooking individuals with deprived circumstances living outside of these areas. It is important to avoid making false claims in the interpretation of results given the usefulness of area level analyses for understanding health inequalities. Bailey et al. (2003) recommend that deprivation is more accurately measured at the smallest spatial scale available as this increases the likelihood that areas are socioeconomically homogenous, and in turn reduces the impact of ecological fallacy.

Similarly, an over emphasis on individuals as the most useful unit of analysis may result in problems associated with the atomistic fallacy (Gatrell and Elliott, 2011). Using individual level data may overlook or misinterpret effects which can be better understood at the level of households, neighborhoods or regions. These include characteristics of the physical, social and economic setting such as; climate, neighborhood poverty or affluence, inequality in living conditions, and quality and quantity of available healthcare services (Macintyre et al., 1993). Ecological research might allow for some impact of the aggregated effect on individual characteristics to be identified at the area level (Seusser, 1994). Many health outcomes vary in relation to a myriad of social, demographic and geographical factors, all of which display distinct patterns that imprint on the distribution of health (Marmot, 2010). As explored, individual ethnicity may have a different significance when it constitutes a minority state than when it denotes part of a majority in the population (Nazroo, 2001). An ecological perspective within research is important; analysing individuals alone may ignore these patterns (Macintyre and Ellaway, 2003).

The exploratory potential of the wide characteristics of the geographical dimension is limited by the fact that it is often generally considered within specific administrative boundaries (Caughy et al., 2007). It is argued that fine-scale, spatially aggregated data are necessary to capture variation in key population characteristics and properly assess geographic inequalities (Rigby et al., 2017). One reason to account for why there may have been few studies that apply spatially explicit analyses for understanding health inequalities is linked to data availability. Data is usually restricted in the detail offered, with a compromise between geographical

coverage at lower levels and variable choice. A reduction in geographical detail is likely to correspond to a considerably diminished ability to assess how far the populations of (parts of) Britain are becoming more or less similar. For a more complete picture it is necessary to analyse the outcomes at a more sensitive scale (Lloyd, 2014; Lloyd, 2015). Evidence suggests growing risk for the health and well-being of coastal (Depledge et al., 2017) and rural communities (Sabater et al., 2017) however, the geographical isolation and comparatively small populations of these communities means they are often not identifiable when using larger geographical units or fixed administrative boundaries. Cummins (2007) and Caughey et al. (2007) caution that the small local area may not always be the most pertinent scale of influence on health as people are influenced by areas further away as well as by their immediate surroundings. It is important to not consider areas as ‘islands’ unaffected by neighbouring units (Sridharan et al., 2007). The scale of analysis conducted at the small-area level must be suitably large enough to encompass this influence (Caughey et al., 2007).

2.10.3 Assessing change over time

Analyses of change over time in small geographical areas are restricted by the availability of common variables and geographical zones (Martin, Dorling and Mitchell, 2002). The geographical zone most applicable to analysis may not be the geography at which data are collected or available, resulting in mismatch between aims and results. There is a tension between collecting information that is currently relevant and maintaining contemporary best practice, and yet still enabling comparisons with earlier time periods (Rees et al., 2002). The type, topics and range of questions that are asked at different time points, changes in data definitions and the ways in which data are released are another set of challenges when analysing change through time (Norman, 2010; Rees et al., 2011). Challenges relating to geography include changes in the scale and type of areas for which data are disseminated, and changes in the boundary definitions and names of areas for which data are available (Norman, 2010b). Such changes, if not taken into account, can skew analyses of change over time through aggregation and the effects of scale (Openshaw, 1983).

An example of these temporal challenges can be seen with the LLTI question used in this thesis. In 1991, individuals are asked whether they have any long-term illness, health problems or handicaps which may limit their daily activities or the work they can do (Office of Population Censuses and Surveys, 1991). In 2001 use of the word ‘handicap’ is replaced by ‘disability’ (ONS, 2013b). Bajekal et al. (2004) report that the negative stigma associated with the word ‘handicap’ may have led to underreporting of the prevalence of LLTI by respondents

in 1991 (Bajekal et al., 2004). The addition of a General Health question in the 2001 Census may also have caused individuals to be more aware of their health, possibly leading to wider reporting of limiting conditions in 2001 that was not captured in 1991 (Bajekal et al., 2004). The response options to the LLTI question were expanded from two to three in 2011 and respondents were asked to make a judgement regarding the extent to which their activities are limited by their illness, with the ‘yes’ response option from 2001 changed to ‘yes, limited a lot’ and ‘yes, limited a little’ (ONS, 2013b). It is not possible to establish how distinguishing between ‘limited a little’ and ‘limited a lot’ impacted on responses (Wright et al., 2017). In particular, respondents who previously would not have reported a limiting long-term illness but under the 2011 question would judge that they are limited ‘a little’ is especially problematic for dichotomising groups for comparability (ONS, 2013b). Such limitations are fairly minor compared to other measures and the questions are sufficiently similar to draw indicative insights on change over time (ONS, 2013b).

Non-comparable boundaries can be problematic for detecting change over time. Researchers have made cases for consistent population surfaces that allow direct comparison of data for different time periods (Martin, 1996). In many studies, comparable data boundaries have been achieved using areal interpolation techniques of counts from the original (source) zones to a set of zones which are common for the time periods being compared (Gregory, 2009; Norman, 2010a). Gridded products have been developed in many contexts including in the US (Mennis, 2003) and across Europe (Gallego, 2010; Lloyd et al., 2017a). One key benefit of gridded population counts is that the analyses do not depend on geographies which were constructed based on the population distribution at one time point. For example, Output Area (OA) zones used in one year will tend to be split if their population increases markedly (Lloyd et al., 2017b). There is considerable potential in placing a wide array of datasets onto a common gridded geography. Grids allow a straightforward assessment of change through time without using irregular zones as all units are of the same size and shape (Lloyd et al., 2017a). Grids represent populations which are arguably more true to the real world and, unlike standard areal data which tend to cover all land areas in the study region, where there are no people there may be no cells (Lloyd et al., 2017a). Using grids, scale effects can be explored through simple aggregation of cells as the spatial resolution is coarsened (Lloyd et al., 2017a).

Gridded populations have been used to assess and monitor population trends and health outcomes (Shuttleworth and Lloyd, 2009; Lankila et al. 2013). Shuttleworth and Lloyd (2009) utilise grids to assess for residential segregation amongst Northern Ireland’s communities. In

this investigation, gridded cells allowed an assessment of change through time, demonstrating that Northern Ireland became more residentially segregated between 1971 and 2001, but that residential segregation in 2001 remained approximately at its 1991 level (Shuttleworth and Lloyd, 2009). Lankila et al. (2013) examined the association between health and well-being with movers across rural and urban areas in Finland, utilising 1km² gridded cells to provide a high level of geographic detail. Recent examples of gridded populations for Britain include; grids developed by Murdock et al. (2015) which use 2001 Census, postcode and building data and cover England and Wales; a Britain-wide grid product developed by Reis et al. (2016) using Census and land cover data; and, the UK PopChange project developed by Lloyd et al. (2016; 2017).

2.10.4 ‘PopChange’

The need for a population surface is driven by changes in Census output geographies as comparisons of Census variables across multiple time points are hampered by changes in output zones (Gregory, 2009; Norman, 2010a; Lloyd et al., 2017a, 2017b). Several studies have utilised standard Census zones with counts reallocated from source zones to a common target geography (Norman et al., 2003; Norman, 2010a; Norman and Darlington-Pollock, 2017). This thesis makes use of freely available 1km² gridded ‘PopChange’ population surfaces (Lloyd et al., 2016; Lloyd et al., 2017a). Links to the ‘PopChange’ resource and other data sources utilised in this thesis can be found in Appendix D, page 184.

The ‘PopChange’ project (Population Change and Geographic Inequalities in the UK, 1971-2011) is an Economic and Social Research Council (ESRC) funded project which has developed geographically consistent sets of counts derived using data from the 1971, 1981, 1991, 2001 and 2011 population Censuses of England and Wales and Scotland. Gridded estimates were generated from population data for each Census and for the smallest areal units available; enumeration districts in 1971, 1981 and 1991 and output areas in 2001 and 2011 with postcode centroid intensities used to help reallocate counts from input zones to output grids (Lloyd et al., 2017a). The resource includes a wide variety of variables which are comparable across all of the Censuses for 1971 to 2011 where common variables are available. The processing of data for each Census year and the specific details of the method used are provided by Lloyd et al. (2017a). The gridded data available consist of a variety of variables including age, country of birth, ethnic group, employment, car ownership, overcrowding, housing tenure, population density and LLTI. The use of these data bring a new and important perspective to debates about division, inequalities and the ways in which people in Britain live

together or apart. The comparable nature of these data will allow an in-depth assessment of how far and over what scales the population of Britain is distributed by health and how this has changed over time.

2.11 Implications and directions for research

Ignoring the role of geography serves only to restrict any understanding of the patterns and processes that contribute to health inequalities. It is only through place that underlying structures which differentiate the health of the population become visible (Dorling, 2012). While a large body of research has investigated the role of geography for explaining these spatial patterns, the pervasiveness of non-spatial approaches has resulted in an incomplete account for why health is increasingly unequal. As it is widely acknowledged that geography matters for health, not applying a spatial modelling approach to understand health patterning is illogical. Greater use of models such as Spatial Regression, Global and Local Moran's *I*, and GWR may reveal new insights about the drivers of geographical inequalities in health through correctly accounting for the spatial structure of many of these issues.

Throughout the literature, the importance of wider structural and historical processes that operate over many decades to shape geographical inequalities in health have been highlighted. The extent that these factors are incorporated into theoretical and applied analyses of health inequalities has frequently been overlooked or undervalued. This imbalance has important implications, not just in terms of understanding the causes of geographical inequalities in health but also for designing and implementing appropriate, robust and sustainable policy solutions. For example, a large body of research has demonstrated the importance of deprivation for health, however analyses often fail to pick apart the specific aspects of deprivation that matter across localities.

Profiling the changing demographic and socioeconomic characteristics of areas is vital for developing an understanding of the changing nature of deprivation and its impact upon changing health inequalities. There is an inherent need to conduct changing health gradient research from an explicitly geographical perspective that incorporates area histories and change over time. The literature reviewed here especially highlights the importance of the historical context of area deprivation. Few studies have a temporal element, focusing instead on cross-sectional observations often due to a lack of suitable data. However, areas are dynamic and single points in time only reflect snapshots of the short, and longer, term trends influencing their health patterns at any one point in time (Pearce et al., 2018).

2.12 Conclusions

This chapter has reviewed relevant literature on health and neighbourhood socioeconomic deprivation. Exploring these multifaceted concepts demonstrates the importance of taking a geographical approach for understanding health inequalities which was the first research objective of this thesis. Introducing the concepts of health and deprivation has effectively demonstrated why this research is important. Additionally, to provide a theoretical and empirical background for the substantive analysis that follows, this chapter has focused on ascertaining an overview of spatial inequalities literature.

Health inequalities are the systematic, structural differences in health status between and within groups in a population (Marmot, 2010). Health status is not a one-dimensional variable but is produced through a complex interconnectedness of personal, social, economic and environmental determinants, and inequalities arise because of disparities in the conditions in which individuals are born, live, work, grow and age (Marmot, 2010). Health inequality is a product of wider structural inequalities; socioeconomic reality in a given geographical area is the product over time of larger scale, macro-political and socioeconomic factors and how these structural processes are entwined within the histories of places (Pearce et al., 2018; Bambra et al., 2019). It is important to comprehensively think about how, why and to what extent certain areas have very different health patterns, as well as how this contributes to unequal distribution of health inequalities through society and space. Within an environment of stark and persistent spatial inequalities, gaining a greater understanding of the role of place on health and the spatial manifestation inequalities is imperative.

2.13 References

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Chapter 3

A spatial analysis of health status in Britain from 1991 to 2011

In order to develop an understanding about the processes that contribute to changing spatial health inequalities it is first important to gain a detailed understanding of how health has been spatially structured over time. Chapter 3 documents the spatial structuring of health in Britain from 1991 to 2011 including exploring the clustering, mobility and persistence of health outcomes over the twenty year period. This is achieved through the use of geographically consistent ‘PopChange’ data that permits comparisons across time. The findings presented in this chapter provide a comprehensive understanding of how the health of the population of Britain in 1991, 2001 and 2011 was spatially structured; an evidence base that the other chapters of this thesis and future extensions of this work can build upon. This chapter is based upon the journal paper of the same name published in *Social Science and Medicine*, Volume 220, pages 340-352.

3.1 Introduction

Social and spatial inequalities in health across Britain are well documented, with differences in health found between constituent countries (Young et al., 2010), regions (Office for National Statistics [ONS], 2013; Whitehead, 2014), urban and rural communities (Allan et al., 2017), and deprived and more affluent areas (Benzeval et al., 2014; Livingston and Lee, 2014). This chapter explores the spatial structure of health inequalities in Britain over the twenty year period 1991 to 2011, examining the changing health of small areas with differing demographic and socioeconomic characteristics (depicted using an area typology), focusing on areas that have experienced persistent poor health. The results allow the geography of change to be captured, highlighting how health is inextricably linked to geography.

Health inequalities are systematic disparities in health status, or in the distribution of health-relevant resources, between individuals and population groups arising from the conditions in

which people are born, grow, live, work and age (Marmot, 2010; World Health Organisation [WHO], 2010; Public Health England [PHE], 2015) and they have been demonstrated for many outcomes including mental health (Fone et al., 2013), cancers (Rosenberg et al., 1999), cardiovascular disease (Congdon et al., 2009), disability (Spencer et al., 2009) and self-reported health (Young et al., 2010). There is a long tradition of studying health inequalities by examining how the health of populations varies in space and of making comparative studies of population health in particular places (Livingston and Lee, 2014). This has resulted in a large literature on the social and geographical differences in the health of resident populations in different parts of Britain. The existence of a health divide is well established but is expressed in two different ways. On the one hand, there is a demonstrable health gradient among socioeconomic groups such that morbidity and mortality increase from the least through to the most deprived groups (Macintyre, 1993; Marmot, 2010; Whitehead, 2014). On the other hand, there is clear geographic patterning to this disadvantage (Riva et al., 2011; Livingston and Lee, 2014; Dutey-Magni & Moon, 2016).

Neighbourhoods are relevant for assessing health variation because they provide resources related to population health, often with highly localised effects (Macintyre et al., 2005). It is well documented that protective and risk factors for health are not evenly distributed across people or places (Macintyre et al., 1993; Black, 2014). Areas within Britain have population compositions, contextual area characteristics, and differing opportunity structures in the physical and social environment, that make them distinct from other locales and contribute to the existence of geographic health inequalities (Marmot, 2010). People and their health shape, and are shaped by, the places in which they live and inhabit on a regular basis. This is in part because people with similar sociodemographic characteristics tend to cluster in space, and in part because individuals living in the same neighbourhood are subject to common contextual influences (Boyle et al., 2004; Smith and Easterlow, 2005). Some local areas have lower unemployment rates than others (Rae et al., 2016), whilst in some places there is a greater mix of ethnic groups than elsewhere (Catney, 2016), and research suggests increasing spatial age segregation within the UK (Sabater et al., 2017). Thus, the degree of difference between areas varies geographically and between population sub-groups, with spatial health inequalities problematic because they indicate peripheralisation and marginalisation of certain population groups and places (Dorling and Woodward, 1996).

Geographical inequalities link directly to research on residential segregation where the objective is to assess how members of different population groups may live together or apart

(Shuttleworth and Lloyd, 2010). Social and spatial polarisation can be broadly defined as the widening gap between groups of people in terms of their economic and social circumstances and opportunities (Dorling and Woodward, 1996). Being able to measure change in this is crucial in assessing whether the population has become more or less similar over time and how it is geographically organised. Although the study of geographic variations in health has a long history, exploring the changing spatial structure of health in Britain has previously been limited by inconsistent spatial data which do not allow comparability through time. For the first time, we have available a time series of consistent Census-derived data for small spatial units across Britain ('PopChange', *introduced below*) which has been utilised in this investigation to examine the spatial structure of health inequalities over the twenty year period 1991 to 2011. Specifically, this chapter seeks to enhance understanding of the spatialities of health by exploring the changing spatial structure of health in small areas of Britain, identifying whether 'events' of poor-health cluster in space and over time.

3.2 Methodology and Results

Analysis of local-level changes in populations across Britain is hampered by inconsistencies in the geographies used to report counts; exploration of health status is no exception (Norman, 2010). This chapter details a novel analysis of changes in Census-based self-reported health over small areas of Britain from 1991 to 2011, with a health-based question having been first introduced in 1991. This analysis uses consistent small area units to examine the changing spatial structure of Census-derived, self-reported health over the twenty year period 1991 to 2011, offering the first analysis of change in self-reported health status across Britain over time. Firstly, the data used in the analysis are described. Next, the methods of analysing the changing distribution (evenness and clustering) of poor health over time and the results produced are summarised. The analysis provides a rich picture of the changing spatial variation of health inequalities in Britain.

3.2.1 Data and units of analysis

A limitation for many studies which seek to assess evidence for geographical divides in Britain is that they are generally based on data for large areas, whereas a geographically-refined approach that takes into account the spaces in which people experience their daily lives (and consequently, the scale at which individuals encounter the various determinants of health) might be more revealing. The patterning and distribution of health are examined using consistent 1km² grid cells across Britain containing aggregate Census self-reported health data for 1991, 2001 and 2011. The grid data were generated as a part of the 'PopChange' project (for more information see Lloyd et al., 2016) by overlaying source zones (Enumeration

Districts [EDs] or Output Areas [OAs]) with 1km² grids, using postcode densities to allocate parts of the populations of source zones to grid cells; more details are provided by Lloyd et al.. (2017). Analysis was conducted only on grid cells which were estimated to contain people (in practice, two separate population thresholds – of 0.5 and 25 persons or above - were used, noting that fractions of people are possible when utilising PopChange data) and were consistently populated at the lowest threshold through all three Census time points. Grids offer several advantages over irregular geographies – they are not constructed according to the population structure at any one time point (unlike, for example, output areas) and they arguably allow for a more natural representation of populations, with gaps where there are no people. In addition, gridded data can be interrogated using a wide array of raster analysis tools (Lloyd et al., 2017). Grid data allow for a novel perspective on how far the health of populations of (parts of) Britain are becoming more or less similar. Use of these data made it possible to consider how localities have changed in terms of health status in Britain over the twenty year study period.

Census-based health measures are important indicators of morbidity both in individuals and at area-level, and are widely used to explore the geographies of health (Jylha, 2009; Badland et al., 2017; Wu et al., 2013; Cooper et al., 2015; Putrik et al., 2015). Poor health is measured here by the proportion of people reporting a Limiting Long-Term Illness (LLTI) using ED and OA- level Census data allocated to 1km² cells (as outlined above) for England and Wales, and Scotland for 1991, 2001 and 2011. LLTI relates to health conditions that limit a person's everyday activities or work and is a commonly-used indicator of morbidity (ONS, 2013a). Definitions of LLTI are not consistent across Censuses and it was necessary to aggregate the groups used in 2011 in order to construct consistent groupings for comparison across the Censuses of 1991, 2001, and 2011 (Table 3.1). Based on ONS guidelines, LLTI response options for all Census years were dichotomised into 'Limited' or 'Not Limited' (expressed as a percentage of all people) permitting comparisons between areas and over time (ONS, 2013a). For further information on the data sources utilised in this thesis, please refer to Appendix D, page 184.

Table 3.1 Limiting Long-Term Illness Census questions and responses 1991, 2001, 2011

	Question	Response Options	Output for Analysis
1991	Does this person have any long-term illness, health problem or handicap which limits his/her daily activities or the work he/she can do?	Yes, has a health problem which limits activities.	Limited.
		Has no such problem.	Not Limited.
2001	Do you have any long-term, illness, health problem or disability which limits your daily activities or the work you can do? Include problems due to old age.	Yes.	Limited.
		No.	Not Limited.
2011	Are your day-to-day activities limited because of a health problem or disability which has lasted, or is expected to last, at least 12 months? Include problems related to old age.	Yes, limited a lot.	Limited.
		Yes, limited a little.	Limited.
		No.	Not Limited.

Data from Office for National Statistics.

Previous studies have shown that self-reported health indicators are strong and independent predictors of mortality and morbidity within the population (Jylha, 2009; Putrik et al., 2015), but this association has been found to vary between populations and population sub-groups (DeSalvo et al., 2006). As self-reported measures are subjective, integrate personal expectations of health, and result from a complex aggregation process of several elements and experiences, such measures may be affected by social, cultural, regional and temporal subjectivity to a greater degree than physiological or mortality measures (Senior, 1998; Macintyre et al., 2005). However, self-reported health measurements serve as useful tools for identifying individuals and groups at risk of poor health, and for monitoring health change in populations (Badland et al., 2017) with self-reported measures providing considerable scope for analysis and potential for applications in health planning.

3.2.2 Assessing changing Limiting Long Term Illness rates over time

Before considering how the structure of health inequalities has changed over time, national-level geographical distributions and percentage shares of LLTI across Britain over time are provided for context. The percentage of people reporting a LLTI increased between 1991 (12.17%) and 2011 (18.07%) although data reveal that this increase took place over the ten year period between 1991 and 2001, with all constituent countries, and Britain as a whole, reporting small decreases in LLTI rates between 2001 and 2011 (Table 3.2). Given that the magnitude of increase between 1991 and 2001 was largely uniform across all areas, it has been suggested that higher prevalence in 2001 may be attributable to a change in the LLTI question

wording between Censuses (Wright et al., 2017). As Table 3.1 displays, in contrast to 1991, the 2001 Census specification includes problems which are related to old age, possibly leading to wider reporting of age-related LLTI in 2001 that was not captured in 1991. Additionally, the use of the word ‘handicap’ in 1991 was replaced by ‘disability’. It has been suggested that the stigma associated with the word ‘handicap’ may have previously led to a systematic bias and underreporting of LLTI (Bajekal et al., 2004). This increase in prevalence, set within a trend of increasing life expectancy, may also reflect increased expectations people have about their health (Wright et al., 2017).

Differences between the constituent countries of Britain are noticeable and have persisted through time. Wales consistently has the highest prevalence of activity limitations, a rate that was five percentage points higher than in England in 2011, with similar differences recorded in other Census years. At a regional scale, all regions reported increased LLTI rates over the two decade period (Table 3.2), however regions in the north have similarities in their health profiles and trajectories that make them distinct from the southern regions of England; distinctions between the regions are noticeable and have persisted through time. There is a pronounced concentration of small percentages of LLTI in central and southern England and higher rates in northern urban areas and Wales, with health improving in line with a southerly and easterly direction of travel. Rates remain highest in regions where heavy industry was formally most concentrated, specifically in coal mining areas. Outside of Wales (22.76%), the North East region of England (21.67%) had the highest percentage of activity limitations in 2011. London (14.15%) had the lowest LLTI rate in 2011. A difference of 8.61 percentage points is observed between the top and bottom ranked regions in 2011, a gap which appears to have widened over time from 6.22% in 1991 and 7.85% in 2001, suggesting growing regional health inequality. Exploring how English regions, Scotland and Wales in 2011 compare with 2001 reveals a variable picture; those regions with the highest rates of LLTI saw their rates fall between 2001 and 2011, while regions with the lowest rates of LLTI in 2001 saw increases. London is an exception to this trend and experienced decreases over this decade from already comparatively low rates, becoming the region with the most favourable health in 2011. Furthermore, rates have risen most slowly in London (+3.03%). Economic in-migration is likely to have affected the sociodemographic structure in London towards a more trained and skilful workforce and younger age profile, resulting in more favourable health status (ONS, 2013b).

The spatial variation of health segregation is also investigated using a detailed district classification. By examining health inequalities through an area classification framework new insights into health inequalities in different demographic and socioeconomic contexts and, correspondingly, the potential causes of local health inequalities have been obtained. Small area grid cells were grouped using the ONS 2011 Area Classification for Local Authorities (ONS, 2014a). This classification is a three-tier system comprising of Supergroups, Groups and Subgroups on the basis of 59 demographic and socioeconomic variables drawn from the 2011 Census and has been used extensively in academic research (for example, Lymperopoulou and Finney, 2016) to provide descriptive characterisations of geographic areas. The top tier classification comprising eight Supergroups of areas in the UK is utilised here. It should be noted that this classification covers the whole of the UK but in the analysis here has been applied only to Britain, therefore the ONS classification of ‘Scottish and Northern Irish Countryside’ applies only to Scotland and will, hereafter, be referred to as ‘Scottish Countryside’. For further information about the area classification, and other data sources, used in this thesis please refer to Appendix D, page 184. Figure 3.3 illustrates changes in health segregation across grid cells by district type in Britain since 1991. All area classification types experienced increased LLTI rates over the twenty year period but with a large amount of variation. All regions, excluding ‘English and Welsh Countryside’ (+0.79%) and ‘Prosperous England’ (+0.57%) experienced a decrease in LLTI rates between 2001 and 2011, suggesting that these two, more rural, area types are key locations for worsening health over time, albeit at a comparatively low level. ‘Mining, Heritage and Manufacturing’ (21.05%) and ‘Coast and Heritage’ (20.02%) areas had the highest rates of LLTI of all area types; these area types have had consistently, comparatively high rates of LLTI over the twenty year period, but have also experienced large increases over time.

Table 3.2 Limiting Long Term Illness rates for region and area classification for 1991, 2001 and 2011

	Difference					
	1991	2001	2011	1991 to 2001	2001 to 2011	1991 to 2011
Britain	12.17	18.41	18.07	6.24	-0.34	5.90
Scotland (S)	12.69	20.34	19.67	7.64	-0.67	6.97
Wales (W)	16.17	23.33	22.76	7.16	-0.57	6.59
North East (NE)	15.32	22.74	21.67	7.42	-1.08	6.35
North West (NW)	13.79	20.73	20.24	6.94	-0.49	6.45
Yorkshire and The Humber (YH)	13.30	19.52	18.84	6.22	-0.69	5.53
East Midlands (EM)	11.73	18.42	18.64	6.70	0.22	6.92
West Midlands (WM)	12.24	18.90	18.99	6.67	0.09	6.76
East of England (EE)	10.21	16.21	16.71	6.00	0.50	6.50
London (L)	11.13	15.49	14.15	4.36	-1.34	3.03
South East (SE)	9.95	15.48	15.72	5.52	0.24	5.76
South West (SW)	11.40	18.12	18.43	6.72	0.32	7.04
Business and Education Centres	13.63	19.55	17.91	5.92	-1.64	4.27
Coast and Heritage	12.87	20.12	20.02	7.25	-0.10	7.15
English and Welsh Countryside	11.67	18.74	19.53	7.07	0.79	7.86
London Cosmopolitan	11.76	15.60	13.75	3.84	-1.85	1.99
Mining Heritage and Manufacturing	14.26	21.33	21.05	7.07	-0.28	6.80
Prosperous England	8.84	13.98	14.55	5.14	0.57	5.71
Scottish Countryside	12.05	19.93	19.83	7.88	-0.10	7.78
Suburban Traits	10.76	16.29	15.87	5.52	-0.42	5.11

Authors calculations using PopChange data derived from Office for National Statistics and National Records Scotland data.

Figure 3.1 shows LLTI rates for 1km² grid cells for Britain in 2011, and demonstrates distinctive spatial variability. Appendix C (page 182) contains complementary reference maps that display the location of constituent countries, regions and key localities in Britain. Intrinsic geographical differences in health inequalities across residential contexts are revealed; Wales, western Scotland, north-east England and many coastal areas have distinctly higher rates of LLTI whilst eastern Scotland and inland areas predominantly in southern England have very low LLTI rates. Maps of 1991 and 2001 LLTI percentages [not presented] show broadly similar geographic trends.

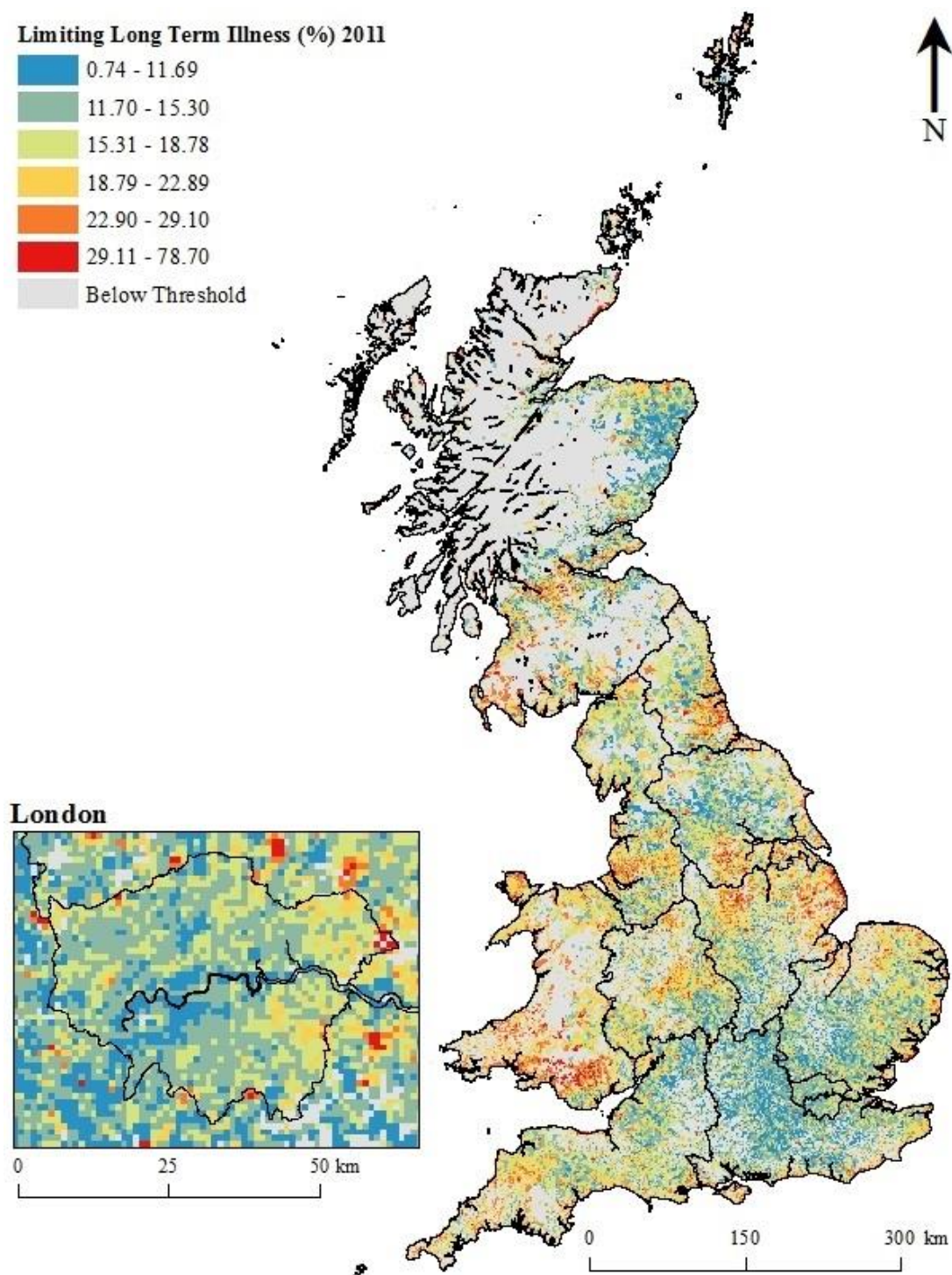


Figure 3.1 Limiting Long Term Illness (%) in Britain 2011

(population threshold of 0.5 persons)

Authors calculations using PopChange data derived from Office for National Statistics and National Records of Scotland.

An analysis of the percentage change in LLTI between 1991 and 2011 (Figure 3.2) reveals distinctive geographic patterning. Large decreases in the percentage share of LLTI in some urban centres especially in central London, Edinburgh, Cardiff, Manchester, Leeds and Sheffield are observed with small increases in LLTI in surrounding suburban areas during this period. Increases in the percentage share of LLTI are found in grid cells which are predominantly in coastal locations including the Lincolnshire coastline, the south-west and northern coasts of Scotland, areas along the coast of East Anglia, the coastline of south east England and the Isle of Wight. Coastal communities tend to have an older age profile than others across Britain (ONS, 2014b). Disproportionate patterns of internal and inward migration, remoteness, lack of investment in infrastructure, high levels of socioeconomic deprivation and seasonal employment have also been highlighted as factors that threaten health in coastal communities (Depledge et al., 2017).

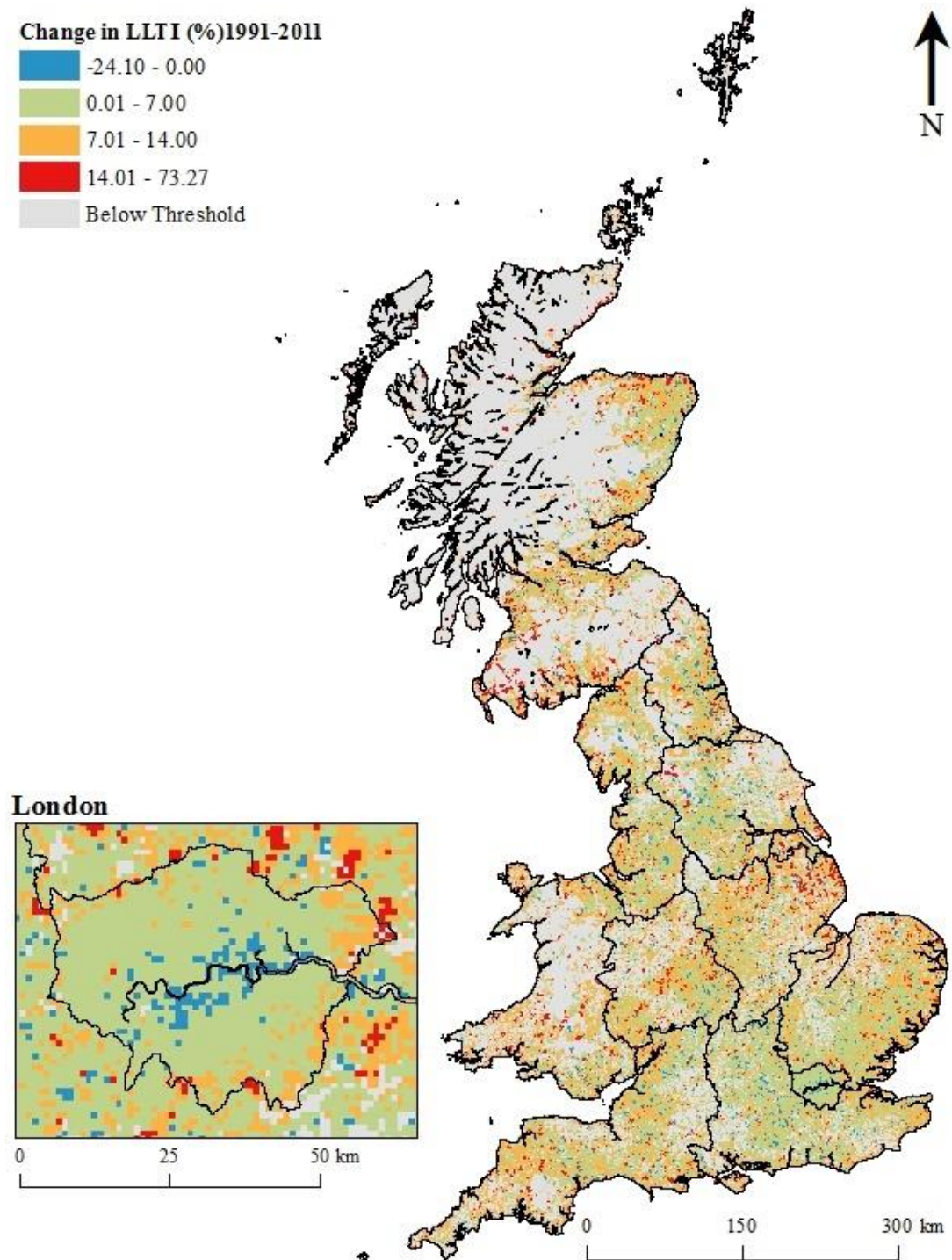


Figure 3.2 Limiting Long Term Illness (%) change in Britain 1991-2011

(population threshold of 0.5 persons)

Authors calculations using PopChange data derived from Office for National Statistics and National Records of Scotland.

3.2.3 Measuring segregation and unevenness with the index of dissimilarity

Measures of segregation are essential tools for the evaluation of social equality, allowing complex structural patterns over time to be described by single measures. The dissimilarity index, hereafter D (Duncan and Duncan, 1955), is applied to assess the distribution (evenness) of people who report LLTI relative to those who do not:

$$D = 50 \sum_{i=1}^n \left(\left| \frac{x_i}{X} - \frac{y_i}{Y} \right| \right), \quad [1]$$

Where x_i and y_i are counts of population in two groups for areal unit i and there are n units. X and Y are the total population counts across the whole of the study area. Multiplying by 50 expresses the share as a percentage where D takes a value between 0 (completely even spread of the two groups) and 100 (all grid cells are 100% LLTI or non-LLTI). Thus, the more the population has spread out, the greater the decrease in segregation.

In 1991 D was 14.10 for Britain (25 persons population threshold). Over the following two decade period, the distributions of those with a LLTI and those reporting no LLTI have become more even. Although Britain as a whole was less segregated by health status in 2011 than it was in 1991, it was very slightly more segregated in 2001 (+0.11%) than in 2011. While global measures demonstrate a trend of decreasing health segregation across small areas, they hide considerable heterogeneity at the sub-national level. To examine this heterogeneity variations in residential health segregation within regions across Britain were explored. Table 3.3 presents the segregation index (D) values for 1991, 2001 and 2011 and the differences over time.

Health segregation at a regional level generally declined rapidly in the 1990s and further decreased in the 2000s, albeit to a lesser degree, but this change is complex and not uniform across regions. Between 1991 and 2001, all regions, with the exception of the South West (+0.09%), reported decreasing segregation. Outside of London, the regions least segregated by health are located in the north. In contrast, slight increases in segregation values in the decade 2001 to 2011 are reported predominantly in the southern regions of England. There has been a large reduction in segregation by LLTI status in Scotland over time (-3.66%), however, it still has one of the highest segregation levels by region in 2011 (13.33%). Levels of segregation in the South East have stayed consistent through the decades, but this region has the highest levels of segregation in 2011 ($D = 13.44\%$).

Table 3.3 Segregation index (*D*) values for region and area classification and differences for 1991, 2001 and 2011

				Difference		
	1991	2001	2011	1991 to 2001	2001 to 2011	1991 to 2011
Britain	14.10	13.59	13.70	-0.51	0.11	-0.40
Scotland (S)	16.99	14.70	13.33	-2.30	-1.37	-3.66
Wales (W)	14.22	13.05	12.28	-1.17	-0.77	-1.94
North East (NE)	12.83	11.50	11.29	-1.33	-0.21	-1.54
North West (NW)	12.00	11.19	11.03	-0.81	-0.16	-0.97
Yorkshire and The Humber (YH)	12.66	11.62	11.77	-1.04	0.15	-0.89
East Midlands (EM)	12.44	12.09	12.34	-0.34	0.25	-0.09
West Midlands (WM)	11.57	10.25	9.72	-1.32	-0.52	-1.84
East of England (EE)	12.77	12.44	12.90	-0.33	0.46	0.13
London (L)	8.79	7.55	7.77	-1.24	0.23	-1.02
South East (SE)	13.82	13.29	13.44	-0.53	0.15	-0.38
South West (SW)	11.88	11.97	12.42	0.09	0.45	0.54
Business and Education Centres	12.38	12.84	13.55	0.46	0.71	1.17
Coast and Heritage	11.2	11.71	12.38	0.50	0.67	1.17
English and Welsh Countryside	12.97	12.37	12.12	-0.60	-0.26	-0.85
London Cosmopolitan	7.96	7.63	8.09	-0.33	0.46	0.13
Mining Heritage and Manufacturing	13.51	11.92	10.77	-1.60	-1.14	-2.74
Prosperous England	12.51	11.54	11.67	-0.98	0.14	-0.84
Scottish Countryside	16.39	13.49	12.04	-2.90	-1.45	-4.36
Suburban Traits	10.98	9.84	9.85	-1.14	0.01	-1.13

Authors calculations using PopChange data derived from Office for National Statistics and National Records Scotland data.

It is, however, important to interpret changes in segregation within the context of LLTI percentage values. Over the study period, LLTI % and *D* decreased in northern regions whilst southern regions of England experienced increased LLTI % and *D*. Furthermore, observed *D* values in the south of England are larger than in the north suggesting geographical inequalities are greater in the south than in the north. Overall whilst LLTI levels are higher in the north of England, Wales and Scotland, differences between neighbourhoods are greater in southern regions of Britain.

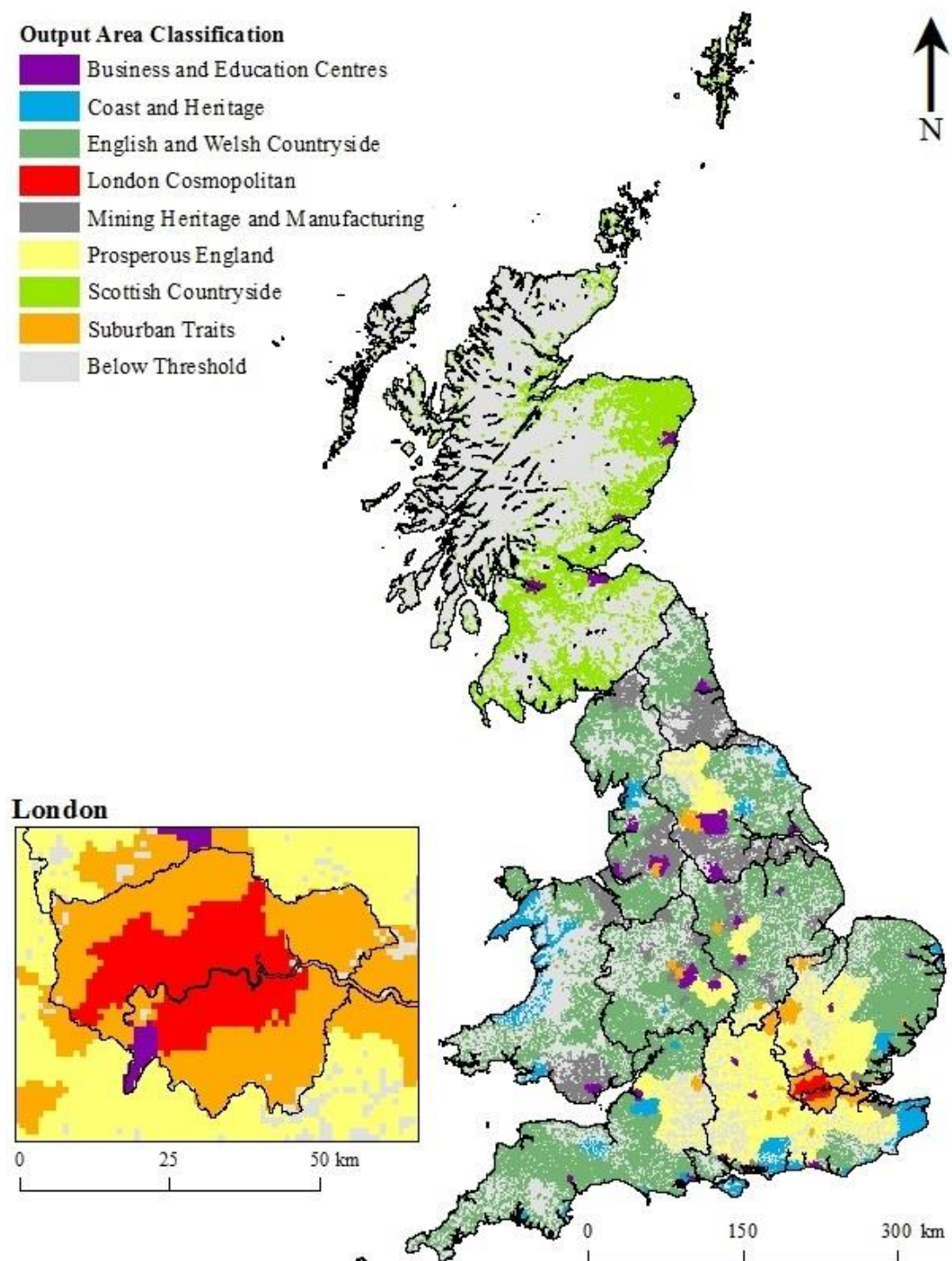


Figure 3.3 Area Classification for Local Authorities Supergroups, 2011
(population threshold of 0.5 persons)
Data from Office for National Statistics

The results confirm that the geographical separation between LLTI and no LLTI groups is varied but small across district types, although important changes over time are revealed. Separation has decreased predominantly in rural settings. ‘Scottish Countryside’ has seen the biggest decrease in D (-4.36%) indicating that those with poor health and those with good health are becoming geographically less separate. Similarly, ‘English and Welsh Countryside’ has seen a decrease in health segregation over time (-0.85). ‘London Cosmopolitan’ has the lowest degree of health segregation (8.09% in 2011) but the separation between LLTI and no LLTI has increased marginally over time (+0.13% between 1991 and 2011). ‘Coast and Heritage’ (+1.17%) and ‘Business and Education Centres’ (+1.17%) also show fairly consistent increases in segregation over the two decade period and are the most highly segregated area types in 2011. In ‘Suburban Traits’ (-1.13%) and ‘Prosperous England’ (-0.84%) there was an overall decrease in segregation, with small increases (0.01% and 0.14% respectively) in segregation between 2001 and 2011. ‘Mining Heritage and Manufacturing’ areas have experienced the largest decrease in segregation over time (-2.74%), a decline that has occurred consistently over the decades to become one of the least segregated area types by 2011 (10.77%).

The results discussed so far are aspatial and make no reference to the spatial configuration of values which could be geographically clustered or dispersed across Britain. The remainder of the analysis focuses on the spatial structure of poor health, and an assessment of clustering using the Moran’s I spatial autocorrelation coefficient is discussed next.

3.2.4 Measuring clustering using Moran’s I

With traditional aspatial segregation measures, the index values obtained will be identical if the values attached to the grid cells are randomly reallocated to other grid cells (Lloyd, 2010). Local measures of spatial autocorrelation have been applied that enable the exploration of local variations in residential health segregation across Britain. Previous studies have treated neighbourhoods as independent geographical units, however, the wider spatial context in which a neighbourhood is situated is increasingly recognised as influential for health (Zhang et al., 2011) but known to be spatially variable (Livingston and Lee, 2014). In this section, global and local spatial autocorrelation is measured using variants of Moran’s I in order to identify temporally consistent spatial clusters of LLTI across Britain, and examine how this patterning has changed over time (1991 to 2011).

Global spatial autocorrelation has been employed to measure how LLTI rates in each small area compare with its neighbours and with more distant areas, giving an indication of the degree of spatial concentration of health status across Britain. There are a variety of spatial autocorrelation (and thus spatial dependence) measures. One of the most widely applied measures of autocorrelation is the I coefficient developed by Moran (1950):

$$I = \frac{n \sum_{i=1}^n \sum_{j=1}^n w_{ij} (y_i - \bar{y})(y_j - \bar{y})}{(\sum_{i=1}^n (y_i - \bar{y})^2) (\sum_{i=1}^n \sum_{j=1}^n w_{ij})} \quad [2]$$

Where the values of y_i (of which there are n) have the mean \bar{y} and the proximity between locations i and j is given by w_{ij} . Here, this is a geographical weight set to one when locations i and j are neighbours and 0 when they are not; this is termed queen contiguity. The I coefficient measures covariation in LLTI at the multiple locations across the entire study area. A randomised simulation procedure was used to estimate the statistical significance of I ; the process was based on 9,999 random spatial reconfigurations of the data values. Moran's I was then computed for each of these randomised data values and the observed value of I was compared to the distribution of the I values derived from the randomised data. Autocorrelation analyses were conducted using the freely available software package GeoDa™ (Anselin et al., 2006). The Moran's I values generated for LLTI rates for 1991 (0.633), 2001 (0.636) and 2011 (0.653) were highly significant ($P < 0.001$) and indicate quite a strong degree of positive spatial association; small areas with similar rates of LLTI tend to occur next to each other (i.e. they form spatial clusters). Furthermore, there is little change over the decades with LLTI Moran's I increasing slightly, but steadily, over time. This trend is fairly weak but it suggests that the degree of spatial clustering of LLTI rates may be growing.

In global tests for autocorrelation, it is assumed that the relationship between nearby or connected observations will remain stationary across the study area (Lloyd, 2010). However, such an approach masks any variation in the spatial structure of the variable of interest. For this reason, a spatially explicit variant of Moran's I which assesses the degree of similarity of values to neighbouring values is implemented (one of a set of Local Indicators of Spatial Association; LISAs) detailed by Anselin (1995):

$$= z_i \sum_{j=1}^n w_{ij}, j \neq i \quad [3]$$

Where z_i are differences of variable y from its global mean ($y_i - \bar{y}$). The weighting scheme is queen contiguity, as applied in computing global I . Spatial clustering techniques have been applied in many epidemiological studies including studies of certain cancers (Rosenberg et

al., 1999), obesity (Flynt and Daepp, 2015) and mental health (Gruebner et al., 2011). The significance of local clusters was determined using the same randomisation approach as employed to assess the significance of global I . The grid cells with significant values of I are then classified according to the nature of the cluster, as detailed below. Figure 3.5 reveals distinctive geographic patterning of poor health that is masked when assessing global indicators. Positive associations (i.e. association between similar values) are observed in areas labelled high-high (i.e. high rates of LLTI in an area surrounded by high values of the weighted average rate of the neighbouring areas), and low-low (low rate in an area surrounded by low values of the weighted average rate of the neighbouring areas). There are also two forms of negative spatial associations (i.e. association between dissimilar values); high-low (high rate in an area surrounded by low values of the weighted average rate of the neighbouring areas), and low-high (low rate in an area surrounded by high values of the weighted average rate of the neighbouring areas). Determining whether a value is statistically significant is assessed by comparing the actual value of for each cell to the value calculated for the same location by randomly reassigning the values (Anselin, 1995). In Figures 3.4 and 3.5 cells assigned 'Not Significant' were included in the LISA analysis and found not to have statistically significant spatial association. This grouping differs from those cells which are 'Below Threshold'; these cells do not contain people above the 0.5 persons threshold and were not included in analysis.

Visually comparing the maps for each individual time point (Figure 3.5a, b, c) displays some distinctive geographical patterning that remains largely consistent over the decades; Birmingham, Liverpool, Manchester, Leeds, Sheffield, Nottinghamshire, Newcastle and the north east have high-high clustering at all three time points. (Full page versions of Figure 3.5 a, b, c and d are provided in Appendix A, page 97 and reference maps that display the location of constituent countries, regions and key localities in Britain can be viewed in Appendix C, page 182). Geographical patterning of low-low clusters is also broadly consistent over time, with this type of spatial cluster predominantly found in inland southern England, and these have clearly become more spatially continuous over time. A distinctive band of low-low clustering is also located on the west coast of Scotland that appears to have contracted over time. Changes in clusters between 1991 and 2011 are displayed in Figure 3.4.

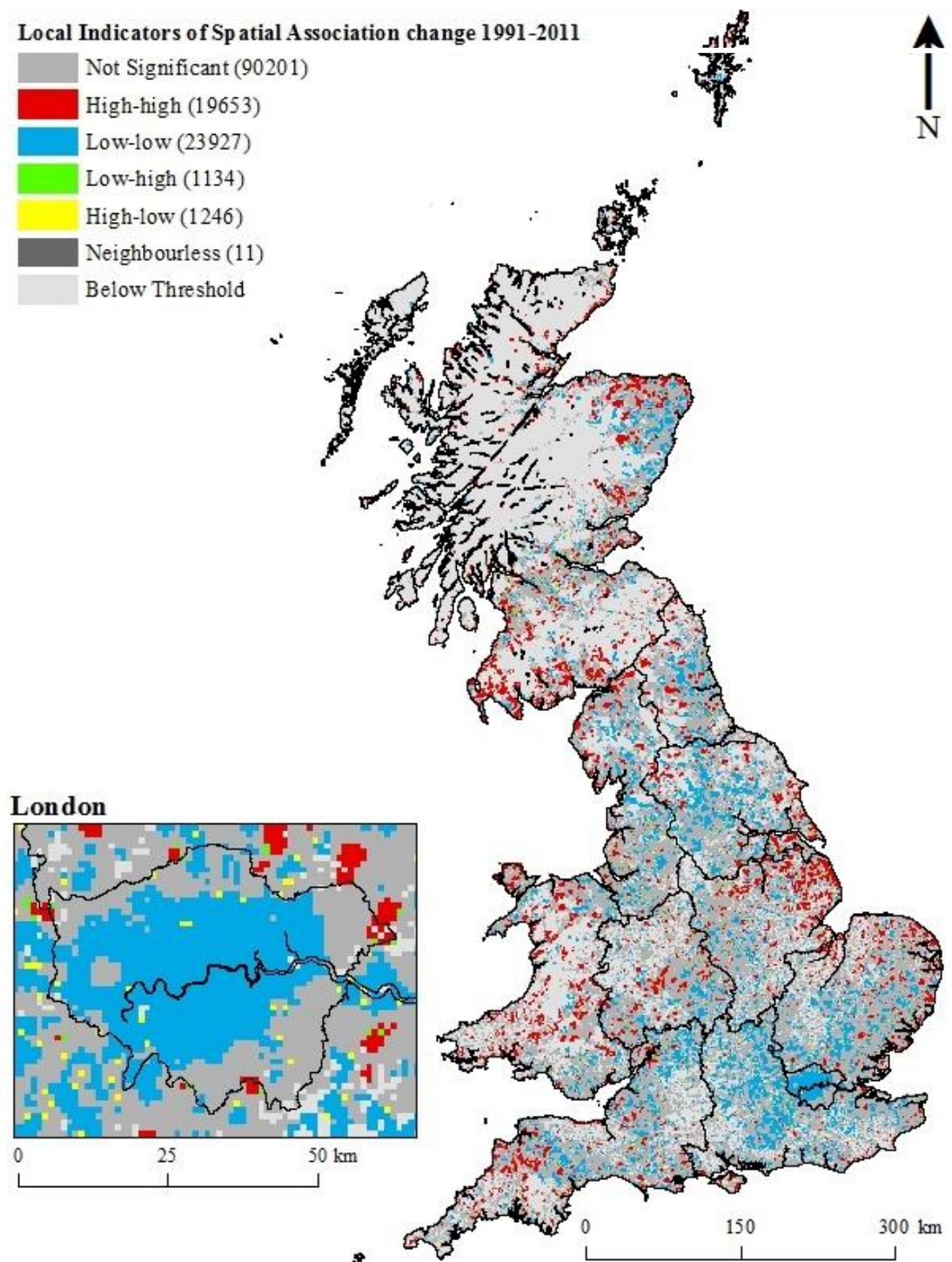


Figure 3.4 Local Indicators of Limiting Long Term Illness (%) change 1991-2011 (population threshold of 0.5 persons)

Authors calculations using PopChange data derived from Office for National Statistics and National Records of Scotland.

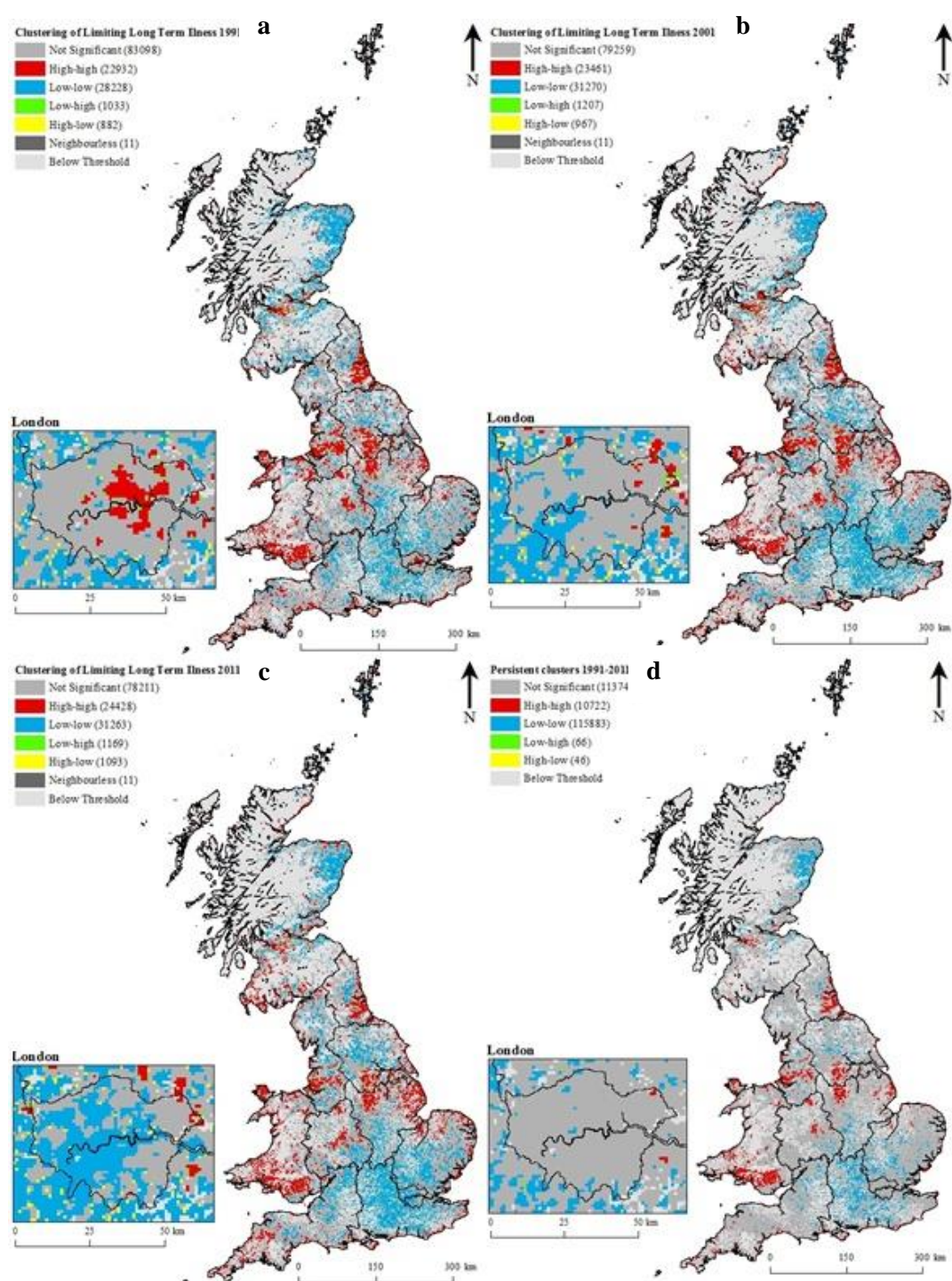


Figure 3.5 Local Indicators of Limiting Long Term Illness (%) (a) 1991, (b) 2001, (c) 2011 and (d) persistent clusters across all three time points (population threshold of 0.5 persons)

Authors calculations using PopChange data derived from Office for National Statistics and National Records of Scotland.

Full page versions of Figure 3.5 a, b, c and d are provided in Appendix A, page 97.

Several marked changes over time are also apparent. There is pronounced change over time in London with high mobility of LLTI clusters observed. In 1991, high-high clustering was observed in central London, but this cluster type is not present in 2001 where the most common cluster type is non-significant. By 2011 some low-low health clusters had emerged. The extreme shift in health status observed in London is an especially interesting finding given that the geography of inequality is recognised to generally not change particularly quickly over time (Dorling et al., 2007). The west of Scotland has gained high-high clusters over the two decade period with very few visible in 1991. These high-high clusters are concentrated predominantly around the coast. Clustering of poor health in Lincolnshire and along its coastline also appears to have expanded over the twenty year period, and expansion of poor health [high-high] clustering is distinctive in south Wales. Glasgow has had poor health clustering across all three time points but appears less tightly clustered over time. The north east of England has also seen a reduction in the geographical spread of high-high clusters over time.

The use of consistent geographical units identifies that 16.77% of areas have been persistently spatially autocorrelated at all three time points (7.81 % with persistent poor health [high-high clusters] and 8.85% with persistent good health [low-low clusters]). Persistently clustered small areas as seen in Figure 3.5d have a very clear geographic patterning which reveals some important characteristics. It appears that persistent high-high clustering of poor health is mainly located in two specific area types. One area comprises of traditional industrial and mining areas such as south Wales, north east England, Merseyside, south Lancashire and the Yorkshire-Derbyshire-Nottinghamshire coalfield. The other consists of coastal districts which are popular with retirement migrants (ONS, 2014b) and those seeking affordable private rental accommodation (Depledge et al., 2017) including south and south-east coastal resorts, north Wales and the Lancashire coast. Table 3.4 demonstrates how areas which were found to be persistently spatially autocorrelated across all three time points were distributed by area classification type.

Of all area types ‘Mining Heritage and Manufacturing’ areas had the highest rate of persistently clustered small areas over time (28.59%), closely followed by areas classified as ‘Prosperous England’ where 26.19% of grid cells were persistently clustered across all three time points. This suggests that it is cells within these area types that experienced the least change in health clustering over time. Comparatively, ‘London Cosmopolitan’ areas experienced the highest rates of mobility, with 99.18% of grid cells within this classification reported to not be persistently clustered over time. The results identify polarity of cluster types

in some area classification types. For example, ‘Mining Heritage and Manufacturing’ areas have the highest percentage of persistent high-high clusters (27.06%) but have experienced very low proportions of persistent low-low clusters over time. In comparison, 25.86% of cells classified as ‘Prosperous England’ are persistently low-low clustered, with less than 1% of areas within this classification type reporting high-high clustering over time. ‘Business and Education Centres’ experience notably high rates of persistent high-high clustering over time (14.24%) but a comparatively large persistent low-low cluster rate (6.10%) is also present, along with the highest rate of any area classification for persistence in the negative spatial association cluster types. This indicates that these are locations of high diversity, with key implications for addressing spatial health inequalities. Uncovering changing health structure is a unique contribution of this analysis. Table 3.5 demonstrates the mobility of small areas through changing cluster type over the period 1991 to 2011.

In Britain health has become more distinctively spatially clustered over time, with a reduction in variation and greater spatial continuity of clusters evident so that larger sets of neighbouring areas have similar health profiles. Identifying these changes over time is a novel and unique aspect of this work afforded by the spatially consistent ‘PopChange’ data used.

Between 1991 and 2011 the low-low cluster category experienced growth (+3,035 cells) and was the most common cluster type in 2011 (31,263 cells). This growth largely resulted from the movement of not significant clusters becoming low-low clusters, which was the most common type of mobility. Figure 3.5 demonstrates that many of the cells which changed cluster type in this way are located in central southern England and the South East region where low-low clustering has become visibly more spatially continuous over time. High-high clusters also experienced growth (+1,505) largely due to not significant clusters becoming high-high (7.44%). Visualisation of the degree of spatial autocorrelation at the three time points (Figure 3.5) indicates that the locations of cells where such movement took place were those in close proximity to established high-high clusters - predominantly in areas with industrial heritage - such that areas of high-high clustering became more widespread and continuous over time. Research suggests that local spatial health inequalities are especially influential to individual health (Zhang et al., 2011), therefore, exploring local inequalities is vital. Analysis reveals that 710 cells (0.52%) which were high-high clustered in 1991 became low-low clusters in 2011 and 1,359 cells experienced worsening health over time, reflected by their change from low-low cluster classification to high-high.

Table 3.4 Crosstabulation of persistent clustering type by area classification

		Cluster Type						Total (=100%)
		Not Significant	high-high	low-low	low-high	high-low	Neighbourless	
Area Classification	Business & Education Centres	79.31	14.24	6.10	0.32	0.03	0.00	3,461
	Coast & Heritage	80.58	16.05	3.33	0.04	0.00	0.00	7,338
	English & Welsh Countryside	89.15	6.70	4.13	0.02	0.01	0.00	60,411
	London Cosmopolitan	99.18	0.00	0.82	0.00	0.00	0.00	609
	Mining Heritage & Manufacturing	71.41	27.06	1.32	0.21	0.01	0.00	13,860
	Prosperous England	73.81	0.21	25.86	0.00	0.13	0.00	20,278
	Scottish Countryside	84.92	4.23	10.72	0.04	0.05	0.04	26,458
	Suburban Traits	87.63	2.55	9.76	0.03	0.03	0.00	3,760
Total		113,747	10,722	11,583	66	46	11	136,175

Authors calculations using PopChange data derived from Office for National Statistics and National Records Scotland data.

Table 3.5 Crosstabulation Spatial Autocorrelation cluster types 1991 and 2011.

		Cluster Type 2011						Total
		Not Significant	high-high	low-low	low-high	high-low	Neighbourless	
Cluster Type 1991	Not Significant	41.18	7.44	11.52	0.39	0.49	0.00	83,098
	high-high	6.76	9.21	0.52	0.33	0.02	0.00	22,923
	low-low	8.80	1.00	10.65	0.05	0.23	0.00	28,228
	low-high	0.38	0.26	0.02	0.09	0.00	0.00	1,033
	high-low	0.32	0.03	0.24	0.00	0.06	0.00	882
	Neighbourless	0.00	0.00	0.00	0.00	0.00	0.01	11
Total		78,211	24,428	31,263	1,169	1,093	11	136,175 (=100%)

Authors calculations using PopChange data derived from Office for National Statistics and National Records Scotland data.

3.3 Discussion

An assessment of the changing degree of residential health segregation and clustering is important in understanding the spatial structure of health inequalities. Analysis used consistent spatial units to examine how the population of Britain in 1991, 2001 and 2011 was spatially structured by self-reported health, including exploring change. The analysis presented demonstrates quantitatively a complex, yet distinctive, patterning of health inequalities. Between 1991 and 2011 small areas have become less different over time with distinctive spatial concentrations of good health and of poor health that are closely linked with area typology.

As a result of the consistency of the PopChange data utilised in this work, areas which have reported persistent clustering of LLTI over time are also documented. It is well established that traditional industrial areas have poorer health profiles (Whitehead, 2014), and this investigation has demonstrated the extent to which poor health is persistently concentrated in such areas. Persistent clustering of poor health is found to be very distinctly spatially organised with the type of spatial autocorrelation observed very closely associated with area classification type. Britain is characterised by its highly polarised skills structure (Whitehead, 2014). The social and economic changes associated with the structural developments that characterise postindustrialism appear to have had a strong and lasting impact on health contributing to the spatial polarisation of health observed. The decline of heavy manufacturing industries experienced in Wales and the North East, and the relative lack of alternative employment opportunities are possible reasons for this distinctive spatial patterning (Taulbut et al., 2014). Given the established relationship between employment status and health, it is not surprising that uneven economic change has emerged as a theme corresponding to health structuring in Britain. The lasting effects of economic downturn on health appear to be exaggerated in coastal areas by two other distinct factors – post-retirement migration (Wilding et al., 2016; Depledge et al., 2017) and a disproportionate quantity of low quality, privately-rented accommodation (Ward, 2015).

Age is an important mechanism of residential location and, through propensity to move, spatial sorting (Sabater et al., 2017). As might be expected, the likelihood of reporting an LLTI is closely associated with age (ONS, 2014b). Interestingly, recent research from England and Wales reveals that spatial separation between older (65+) and younger (25-40) age groups has increased over the last 20 years (Sabater et al., 2017). The younger age structure of London's population may partly contribute to this region's more favourable health status. Other likely

contributing factors are a healthy worker effect resulting from the job-creating regeneration occurring in London during the first decade of the 21st Century (ONS, 2013a). In addition, the attraction of migrants from other parts of the UK and from abroad to take up these employment opportunities in London is also likely to affect the sociodemographic structure towards a more highly educated, younger, and consequently healthier, profile (Green et al., 2015).

Research on migration and migration destinations using UK Census data suggests that health selective migration is an important factor driving the spatial clustering of morbidity in Britain (Norman et al., 2005; Wilding et al., 2016). Migrants are not a random subset of the population, and the social and demographic characteristics of migrants are likely to be quite different from those of non-movers (Norman et al., 2005) with population subgroups such as the young (Riva et al., 2011), highly qualified (Green et al., 2015) or affluent more likely to migrate (Champion, 2012). The literature has, in particular, examined ‘health selective’ residential migrations as life course processes of selection whereby migration acts as a systematic internal sorting process with individuals of the best health migrating to the areas that contain the healthiest individuals (and vice versa) (Boyle et al., 2002; Norman et al., 2005; Green et al., 2015). The impact of such movement raises poor health in the more deprived ‘origin’ areas, creating ‘residual polarisation’ (Norman et al., 2005; Brown et al., 2013). This is reinforced as people in poor health are more likely to migrate to the clusters with poorer health profiles (and associated lower social characteristics) (Green et al., 2015), contributing to the widening spatial health inequalities that continue to be observed across Britain. Furthermore, individuals suffering from poor health may be selectively drawn into health-damaging environments or at risk of displacement, or exclusion, from health promoting environments (Smith and Easterlow, 2005). As health is multifaceted with many determinants, attempting to explain the causal mechanisms underpinning the changing spatial structuring of health in Britain is complex. A framework that explains how resources, accessed by individuals through various domains, and at different spatial scales, are transformed into distinctive geographic health inequalities is the subject of ongoing work.

3.3.1 Limitations

Analysis has successfully mapped the changing spatialities of LLTI change in Britain over time and is novel in demonstrating the persistence of clusters of poor health and the way in which these clusters have changed. There are, however, some caveats which should be noted about the findings reported. Although areas used were consistent over time, the characteristics of the population within cells may have changed. In isolation, the evidence presented in this

chapter does not allow an assessment of why the LLTI status of areas may have changed. Furthermore, as self-reported measures of health are subjective and result from a complex aggregation of experiences and comparison, such measures may be more effected by social, regional and temporal subjectivity than physiological or mortality measures. Additionally, definitions of LLTI are not consistent across Censuses and the changing LLTI question possibly resulted in wider reporting of LLTI in 2001 that was not captured in 1991. It should also be noted that the area classification used in analysis refers to the most recent Census period (2011) and consequently, may not be fully applicable to all cells across all periods. Since this analysis sought to explore how the same areas changed over time it was not possible to apply a separate area classification for each time point and results should be interpreted in consideration of this. Nevertheless, the results presented in this chapter hold considerable advantages and provides the first geographically fine-grained exploration of the spatial structuring of poor health in Britain. This quantitative information can be used as a resource to comprehensively inform future health inequalities work and the evidence presented in this chapter is built upon in subsequent chapters of this thesis.

3.4 Conclusions

Concentrations of disadvantage can have disproportionate effects upon the lives and opportunities of people exposed to them. Therefore, developing methods for understanding the complex spatial structuring of health is important, especially for addressing spatial inequalities in health and for assessing the most appropriate scale at which to introduce interventions designed to improve health and create a more equal society. In evidencing the geographies of health inequalities over time this analysis makes unique contributions to understanding the spatial structure of health, raising many questions about the formation and impact of inequalities and their wider geographies. The results presented have successfully quantified the nature of the spatial structure of health in Britain from 1991 to 2011. Overall decreasing unevenness values, coupled with increased positive spatial association, suggests that neighbouring areas are becoming more similar – the distinction between areas characterised by poor health or by good health is decreasing.

The ‘PopChange’ project has offered a new level of insight into changing population health and geographic inequalities which has not been available before. Unrivalled comparable Census data together with the ONS classification presents evidence of the changing spatialities of health across Britain that have not previously been documented comprehensively. This work captures the diverse nature of changing health inequalities at a geographically detailed scale. Health status is not one-dimensional; the health and well-being of individuals is

influenced by a range of factors, both within and outside of individual control (Brown et al., 2012), consequently, assessing health change over time is complex.

Before the processes which contribute to spatial health inequalities can be explored comprehensively it was first important to gain a detailed understanding of how health inequalities in Britain have been spatially structured over time. This analysis has demonstrated that health varies spatially; locally, regionally and nationally, highlighting how health is inextricably linked to geography. Although regional disparities require addressing, evidence for variation in the spatial structure of the poor health at a very fine spatial scale is also presented, which a regional-only focus would fail to tackle. Spatial inequalities in health are a complex mix of demographic, economic, social, environmental and political processes (Marmot, 2010). Associations between the chances of developing a LLTI and age (Marmot, 2010), gender (Wright et al., 2017), social class and employment status (Chandola and Marmot, 2010; Cooper et al. 2015) are also clear. There is an extensive literature on various aspects of spatial segregation and health inequalities in Britain (Norman et al., 2005; Lymperopoulou and Finney, 2016), however, the way in which these demographic, socioeconomic and geographic factors interact over time to create the distinctive geography of health inequalities observed is less clearly understood. More work is required to fully explore and explain why this spatial structuring is observed. There is a need to take a modelling approach and, in line with the aims of this thesis, analysis in Chapters 4 and 5 begin to address this by building on the findings presented here.

3.5 References

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APPENDIX A

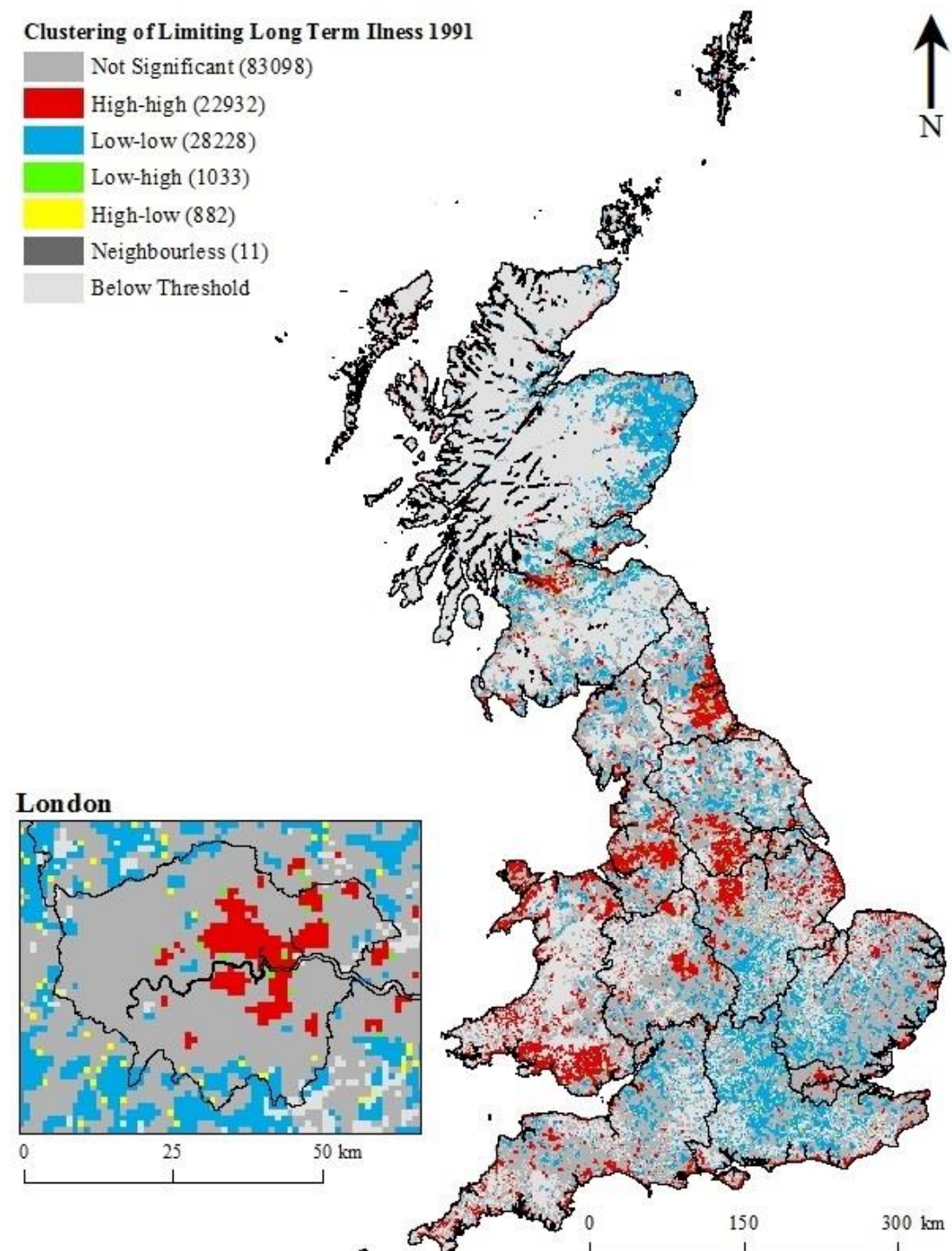


Figure 3.5a Local Indicators of Limiting Long Term Illness (%), 1991
(population threshold of 0.5 persons)

Authors calculations using PopChange data derived from Office for National Statistics and National Records of Scotland.

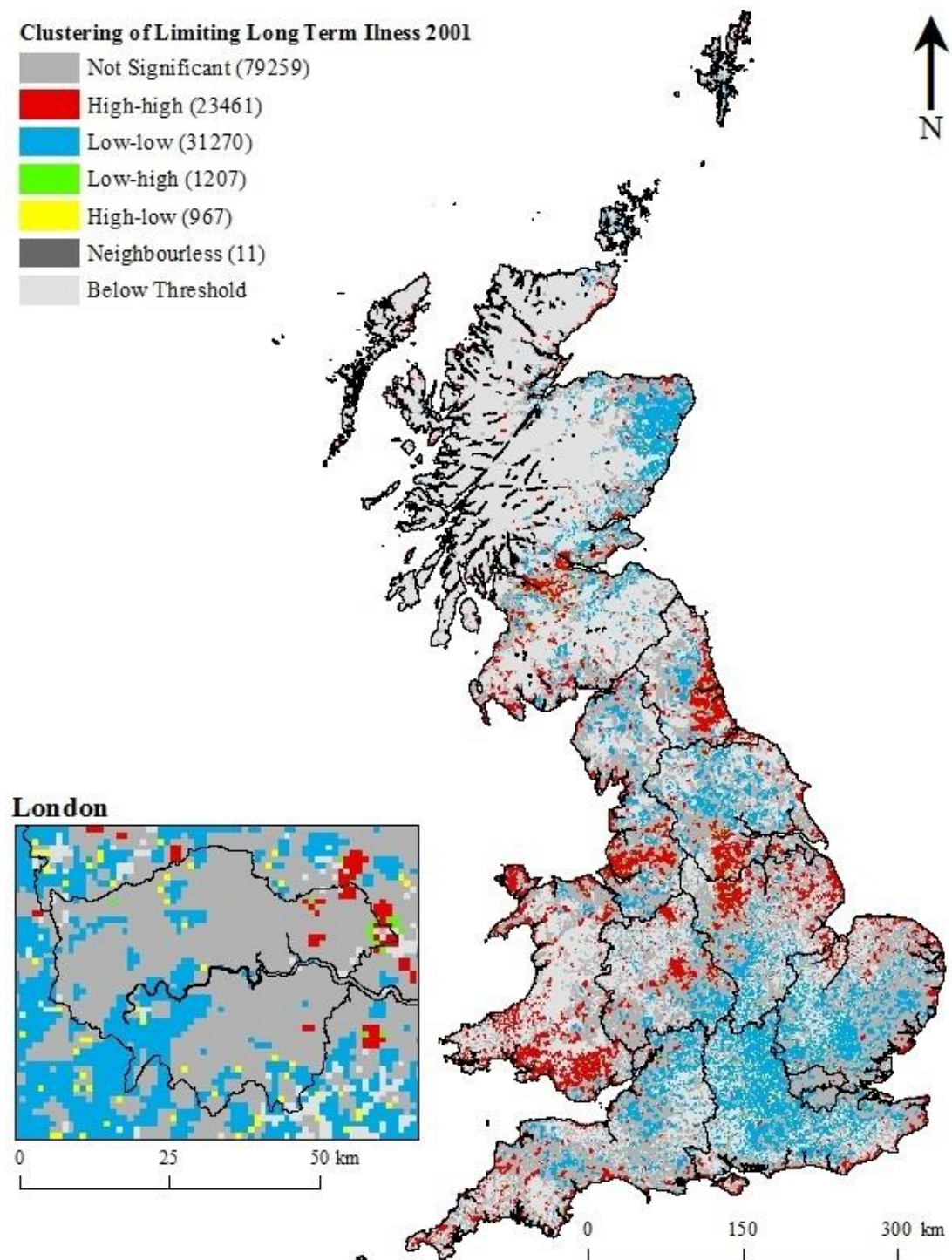


Figure 3.5b Local Indicators of Limiting Long Term Illness (%), 2001
(population threshold of 0.5 persons)

Authors calculations using PopChange data derived from Office for National Statistics and National Records of Scotland.

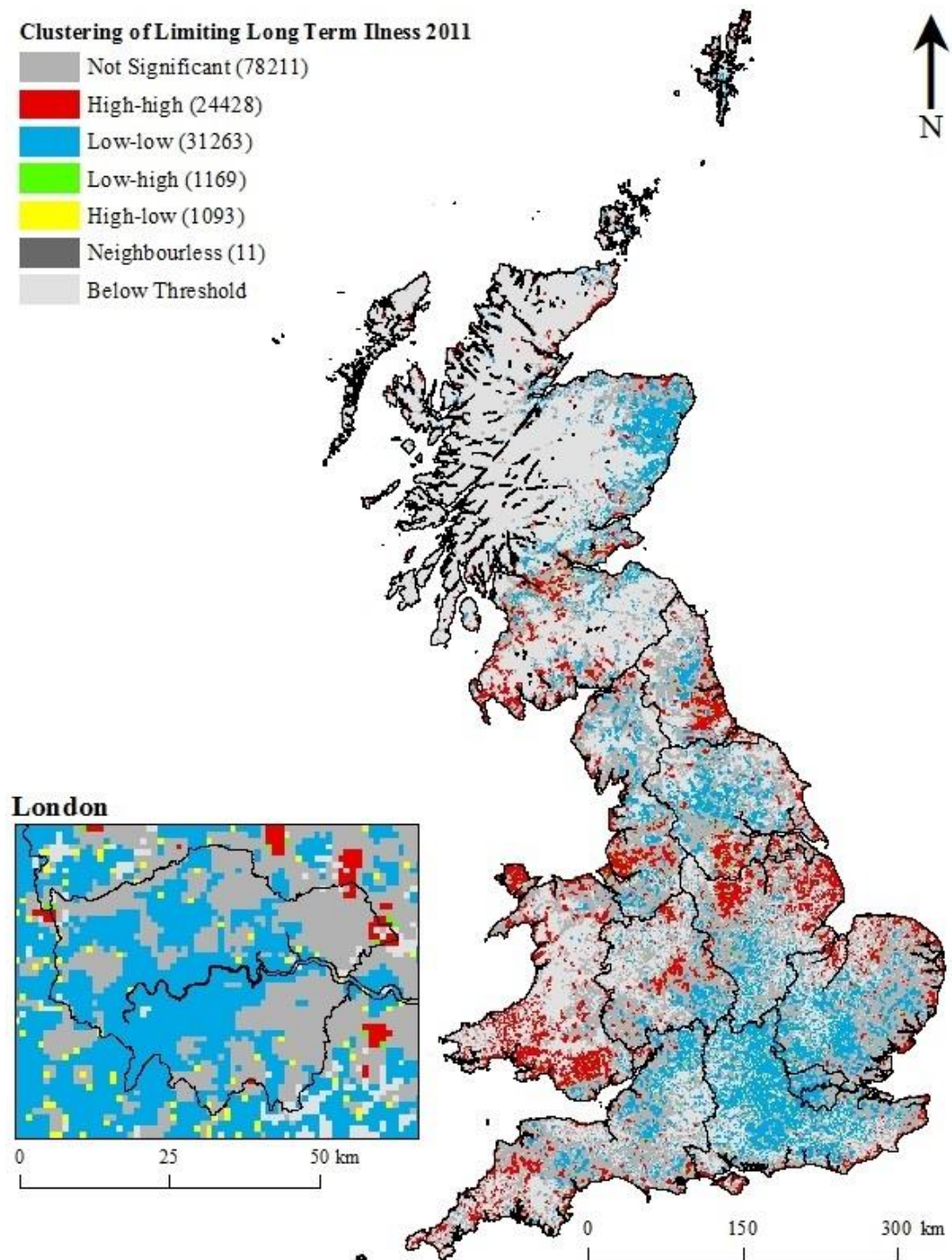


Figure 3.5c Local Indicators of Limiting Long Term Illness (%), 2011

(population threshold of 0.5 persons)

Authors calculations using PopChange data derived from Office for National Statistics and National Records of Scotland.

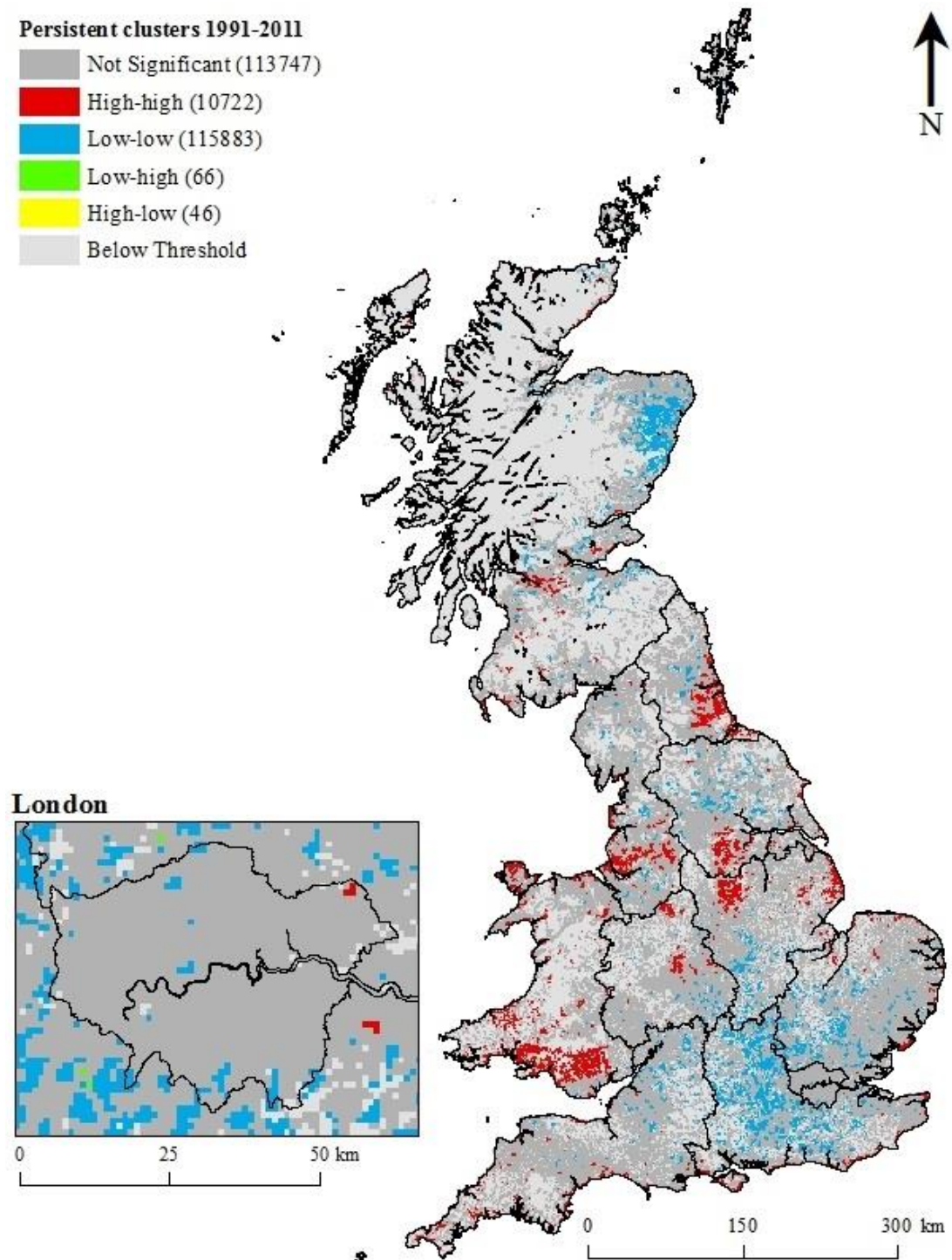


Figure 3.5d Persistent clusters across all three time points

(population threshold of 0.5 persons)

Authors calculations using PopChange data derived from Office for National Statistics and National Records of Scotland.

Chapter 4

Exploring the histories of health and deprivation in Britain, 1971 to 2011

Chapter 3 explored how the health of the population of Britain in 1991, 2001 and 2011 was spatially structured providing comprehensive evidence of the changing spatial distribution and clustering of Limiting Long-Term Illness (LLTI) across Britain over time. In line with the overall aims of this thesis, profiling area deprivation change and exploring the association between deprivation and spatial inequalities is an important next step. Chapter 4 builds on the evidence presented in chapter 3 to investigate the processes that contribute to changing spatial health inequalities, exploring how differences in health are perpetuated through wider socioeconomic and spatial inequalities and how this changes across space and over time. This chapter examines the changing spatial structure of self-reported health in Britain from 1991 to 2011, against a backdrop of 1971 to 2011 area deprivation and social indicators and is based upon a journal paper of the same name currently under review at *Health & Place*.

4.1 Introduction

Pervasive and persistent socioeconomic gradients in health which manifest geographically are well documented within Britain (Acheson, 1998; Macintyre et al., 2005; Marmot, 2010, Whitehead, 2014). Such gradients in health exist across the social spectrum, rather than there being a straightforward divide between those who are deprived and those who are not (Office for National Statistics [ONS], 2014). Those in the most socioeconomically advantaged positions are found to have the best health, and conversely, those with the most deprived circumstances have the poorest health outcomes (Benzeval et al., 2014; ONS, 2014). This has been demonstrated for many health outcomes including cardiovascular disease and diabetes (Kavanagh et al., 2010), respiratory diseases (Ellison-Loschmann et al., 2007) and low birthweight (Krieger et al., 2003). Despite targeted and substantial public health investments designed to reduce such inequalities, relative inequalities continue to widen as improvements in the least-deprived localities continue to be relatively larger than the improvements in the

most deprived places (Marmot, 2010). Understanding inequalities not only at a single point in time but also across generations in a community or geographical location (Pearce et al., 2018) is key to illuminating the processes through which spatial inequalities are being maintained and how they might be successfully reversed.

In seeking to understand the influence of place on health, the role of deprivation is crucial. Area level deprivation may lead to disparities in health outcomes by shaping differential access to resources that can mitigate the risk of poor health outcomes (Bécares et al., 2012). Areas are not static; their contextual and compositional characteristics change over time and in a related manner (Bernard et al., 2007; Gatrell and Elliott, 2009). Poor health outcomes may be the product of cumulative exposure to disadvantage, exposure during sensitive or critical periods in the life course, or both (Jivraj et al., 2019). Previous studies have demonstrated that the experience of people living in deprived areas can be very different (Macintyre et al., 2005). In some neighbourhoods high levels of deprivation have been stable over a long time period, in others a demographic change and economic fluctuations may have resulted in marked increases in levels of deprivation (Lloyd et al., 2015). Ecological research can allow for some impact of the aggregated effect of individual characteristics to be identified at the area level (Seusser, 1994). Many health outcomes vary in relation to a myriad of social, demographic and geographical factors, all of which display distinct patterns that imprint on the distribution of health. For example, the association between individual deprivation and health might also vary in relation to the aggregated socioeconomic profile of the population which evolves over time (Nazroo, et al., 2007; Zhang et al., 2011). An ecological perspective within research is important; analysing individuals alone may ignore these patterns (Macintyre and Ellaway, 2000). Profiling changing demographic and socioeconomic characteristics of areas is vital for developing an understanding of the changing nature of deprivation and its impact upon changing health inequalities. There is a need for place-based approaches which recognise a lifecourse perspective; that the associations between health and place are a set of interrelated processes operating simultaneously at various spatial and temporal scales (Lekkas et al., 2017; Bambra, 2018; Pearce et al., 2018).

Health status is multifaceted, with wide ranging mechanisms that characterise the complexity of neighbourhood environments and their influence on health (Macintyre et al., 2005). Consequently, assessing health change over time is complex. Although the pervasiveness of the influence of material and social circumstances in determining health outcomes is recognised, the challenge of disentangling the causal mechanisms by which these determinants exert themselves on inequalities through a myriad of biological, behavioural, environmental

and psychosocial pathways is subject to ongoing research. Chapter 3 demonstrated the diverse nature of the changing spatialities of health across Britain at a fine geographical scale. Given the pervasive and persistent health gradient, profiling deprivation change and exploring how this is linked with changing health outcomes is an important next step. By measuring how levels of deprivation and poor health have changed in areas over several decades, analysis presented here begins to unpick how change in deprivation and in other characteristics of populations directly influence health status.

4.2 Methodology

4.2.1 Consistent geographies

Studying how areas have changed over time is problematic due to inconsistencies in the definitions of geographical zones which often are not comparable over time. Removing issues of inconsistent boundaries through the use of gridded zones it is possible to generate directly comparable measures of areas to assess how they have evolved over time, allowing the interconnectedness of health status and deprivation to be identified. The analysis uses consistent 1km² units to examine the changing spatial structure of poor health within Britain, and explore how this is associated with changing deprivation.

It is acknowledged that areas, especially when exploring multifaceted concepts like health and deprivation, might ideally be identified in ways which are not constrained by administrative or otherwise arbitrarily drawn boundaries (Chatterton and Bradley, 2000). The utility of devising customised geographies of deprivation (Cockings and Martin, 2005; Haynes et al., 2007) have been demonstrated. Despite these approaches providing valuable insights, they are time-specific. Without taking a consistent geographical approach to produce comparable results over time it is not possible to assess the extent to which change in health status is associated with changing area characteristics (Norman et al., 2003). Gridded data are not constructed according to the population structure at any one time point (unlike, for example, Output Areas) and they arguably allow for a more natural representation of populations (Lloyd et al., 2017).

Fine-scale, spatially aggregated gridded data provide a novel perspective on health change over time and offer several advantages over irregular geographies for analyses of change. Several studies have utilised standard Census zones with counts reallocated from source zones to a common target geography (Norman et al., 2003; Norman, 2010; Norman and Darlington-Pollock, 2017). The gridded data utilised in this investigation were generated as part of the 'PopChange' project (for more information see Lloyd et al., 2016 and Lloyd et al., 2017)

which uses postcode densities to allocate parts of the populations of source zones to consistent 1km² grid cells. Using 1km² sized grids provides a very fine geography allowing local detail in the relationship between health and deprivation to be explored. As grid cells have a constant size, their populations vary markedly, and population estimates can be a fraction. For this reason a threshold approach which draws on the Northern Ireland Census grid square product (Shuttleworth and Lloyd, 2009) was experimented with. Fractions of people are possible when utilising ‘PopChange’ data and only cells which are consistently populated at 0.5 persons and above across the study period (1971 to 2011) are included in the analysis. Gaps where there is no population present allow for a more natural representation of the spread of population across Britain; empty cells include, for example, large unpopulated areas in the highlands of Scotland. ‘PopChange’ data are available from 1971 and although LLTI was not recorded in the Census until 1991; where available, deprivation and demographic variables from 1971 are utilised to explore the cumulative impact of deprivation on health change over time.

4.2.2 Data

The Census is the key source of small area population data in Britain. In this analysis the patterning and distribution of rates of self-reported LLTI were explored using Census-derived, gridded data ‘PopChange’ population surface outputs for 1991, 2001 and 2011. Definitions of LLTI are not consistent across Censuses, and based on ONS guidelines (ONS, 2014), consistent groupings, dichotomised into ‘Limited’ or ‘Not Limited’ (expressed as a percentage of all people) were constructed, permitting comparisons between areas and across the Censuses of 1991, 2001, and 2011. For further information about the ‘PopChange’ resource, or other data sources used in this thesis please refer to Appendix D, page 184.

Previous research has identified a wide-range of factors from the social, economic and physical environment as influential to health status (World Health Organisation [WHO], 2010). These findings were used to inform the choice of explanatory variables utilised in this study. Analysis seeks to assess what characteristics explain LLTI rates, with a particular focus on how far area change over time is important. In addition to variables which measure for different aspects of deprivation (introduced below), Census-derived demographic indicators including population density, age, ethnicity and country of birth were included in analysis.

Quantifying the complexity of deprivation is a major challenge usually addressed through the use of composite indices. The Townsend Index (see Townsend et al., 1988) has been utilised widely in academic research as a measure of deprivation (Norman, 2016). The Townsend Index incorporates information on percentages of: unemployment, no access to a car or van,

non-home ownership, and household overcrowding (more than one person per room) and can be constructed using Census recorded variables for Britain. A summary index of deprivation allows the identification of deprived areas, but as a composite measure, does not permit the distinguishing of specific aspects of the residential environment which are most salient for health. A greater understanding of the interconnectedness of health outcomes and deprivation can be obtained by additionally unpicking the relative contributions of each of the Townsend Index component variables. Such an approach makes it possible to identify to what extent different factors are important and how this changes through time and across space. The four Townsend input variables (two percentages and two logged percentages) were then converted to z scores (percentage-mean/standard deviation) then were summed to derive Townsend Index scores. Positive values of the Index indicate areas with higher levels of deprivation while negative values indicate lower levels of deprivation (Townsend et al., 1988).

4.2.3 Multivariate regression

Using a multivariate regression approach allowed for an exploration of the relationship between health status (LLTI %) and potential explanatory variables. An Ordinary Least Squares (OLS) regression was implemented to study health by residential context, specified as:

$$y_i = \beta_0 + \sum_k \beta_k \chi_{ik} + \varepsilon_i \quad [4]$$

Where y_i is the percentage of the population reporting LLTI for each grid cell i , β_0 represents the intercept β_k is the parameter estimate for variable k , and χ_{ik} is the value of the k^{th} variable for i , and ε_i is the error term. The underlying assumption of the global regression method is that the relationship under study is spatially constant. Thus, the estimated parameter from a global OLS model is spatially invariant. Due to differing compositional and contextual profiles of areas in reality, the relationship between the LLTI and independent variables is likely to vary across space. This spatial component is accounted for through the addition of a spatially lagged dependent variable model (denoted ρ) implemented in GeoDa™ using the queen contiguity (QC) weighting scheme (Anselin et al., 2006). The spatially lagged dependent variable models include terms for independent variables as well as a spatially lagged dependent variable. The model and is specified as:

$$z = X\beta + \rho WZ + \varepsilon. \quad [5]$$

X is the matrix of independent variables, β are the parameters to be estimated, ρ is the spatial autoregressive coefficient, and W is the spatial weights matrix. A spatially lagged regression

model is suitable where it is believed that the values of the dependent variable z are influenced directly by neighbouring values of z . If ρ is zero, the model is equivalent to the standard OLS regression model (Lloyd, 2014). It is noted that the Akaike Information Critereon (AIC), log-likelihood and the Schwarz information criterion have been recommended as the proper means of comparing OLS and spatial regression results (Anselin et al. 2006). These model diagnostics, along with measures used to assess the significance of associations are included in the analysis. When fitting models it is possible to increase the likelihood by adding parameters. AIC and Schwarz criterion attempt to resolve this problem by introducing a penalty term for the number of parameters in the model; the penalty term is larger in Schwarz than AIC (Draper and Smith, 1998). The model with the lowest criterion value is preferred.

In order to fully explore the relationship of deprivation history on health status, several regression models, each exploring a different dynamic of this relationship over time were implemented. Firstly, separate regression models were executed for each time period (1991, 2001 and 2011) where the variables of interest and explanatory variables were exclusively associated with that year (for example, LLTI, unemployment and overcrowding, all pertaining to the 1991 Census). Variables were kept consistent between the models allowing for comparability across time and identification of how persistent the effects of each variable over time were. Next, rates of explanatory variables for previous time periods were also incorporated into the models including variables which were available from 1971 and 1981 (for example, unemployment in 1981 being included in a model which seeks to explain LLTI in 1991). Changes between consecutive Census years were calculated for the same set of explanatory variables and included in the models. For example, Unemployment change between 2001 and 2011 was calculated as Unemployment rate in 2011 minus Unemployment rate in 2001. Additionally, change between non-adjacent years was calculated for any temporal combination for which data were available. For example, Unemployment change between 1981 and 2011 = Unemployment rate in 2011 minus Unemployment rate in 1981. Mapped residuals from multivariate models are also explored.

Initial variable choice was driven by existing work into the relationship between health and deprivation. Once relevant variables were selected and justified based on this theoretical approach they were obtained for every Census time period for which they were available. Change in these variables was then calculated as described above. An iterative stepwise selection process facilitated through IBM® SPSS Statistics 24 was then implemented in order to identify the temporal combination of variables to utilise. Variables were added according to which was most likely to result in the greatest increase in R^2 , beginning with the variable

(in its most significant temporal format) which demonstrated the strongest association with LLTI%. The remaining independent variables were then added into the model one at a time according to which one was most likely to lead to the greatest increase in R^2 ; this was the variable which had the strongest partial correlation with the independent variable (LLTI % separately in 1991, 2001 and 2011). Linear regression assumes that the data are normally distributed and that there is no correlation between the independent variables (collinearity) and variables included in this process met the selection criteria. Models which included the composite Townsend Index score and those which included the individual components of the indicator were generated separately.

4.3 Results

4.3.1 Descriptive statistics of changes over time

Table 4.1 summarises LLTI rates, the Townsend Index score and its composite components at a national level showing how rates have changed over time. Deprivation is generally shown to have eased over the period due to downward trends in levels of lack of access to a car, household overcrowding and levels of unemployment. Figure 4.1 displays long-term deprivation change between 1991 and 2011. Appendix C (page 182) contains complementary reference maps that display the location of constituent countries, regions and key localities in Britain). Deprivation in most major urban areas including London, Birmingham, Liverpool, Manchester, Leeds, Glasgow and Edinburgh increased over this period. Urban areas were more deprived in 2011 than they were in 1991.

LLTI rates increased from 12.17% to 18.07% (1991 to 2011) with the majority of this increase occurring between 1991 and 2001; all constituent countries, and Britain as a whole, report a small decrease in LLTI rates between 2001 and 2011. Despite these trends, not all people within locations became less deprived or experienced reduced levels of LLTI, with gradients of deprivation and health largely persisting across Britain's constituent countries. The spatial patterning of change over time in LLTI rates (1991-2011) across Britain is displayed in Chapter 3 (Figure 3.2, page 77) and reveals large decreases in the percentage share of LLTI in some urban centres especially in central London, Manchester, Leeds, Sheffield, Edinburgh and Cardiff with small increases in LLTI in surrounding suburban areas during this period. Large increases in the percentage share of LLTI are predominantly found in cells which are in coastal locations including areas along the Lincolnshire coastline, the south-western and north Scottish coast, areas along the coast of East Anglia and the coastline of south east England.

Table 4.1 Descriptive statistics of key variables

	1971	1981	1991	2001	2011	Difference (% change)		
						1991 to 2001	2001 to 2011	1991 to 2011
Limiting Long Term Illness (Limited %)	--	--	12.17	18.41	18.07	6.24	-0.34	5.90
Mean Townsend Index score	1.56	0.79	0.42	-1.28	-1.32	-1.70	-0.04	-1.74
Unemployed (%)	4.08	10.50	9.29	5.34	6.67	-3.95	1.33	-2.62
Not Owner-Occupied (%)	51.67	44.34	33.94	31.71	35.88	-2.23	4.17	1.94
No Car or Van Access (%)	49.02	39.48	33.35	27.47	26.08	-5.88	-1.39	-7.27
Overcrowding (%)	7.21	4.34	2.22	1.88	1.99	-0.34	0.11	-0.23
Age 65+ (%)	13.25	15.03	15.85	15.86	16.53	0.01	0.67	0.68
Aged 14 and under (%)	24.08	20.59	19.17	18.79	17.57	-0.38	-1.22	-1.60
Not-UK born (%)	6.40	6.70	7.30	8.90	13.40	1.60	-11.80	6.10
Not-White (%)	--	--	5.90	8.70	14.00	2.80	5.30	8.10

Authors calculations using PopChange data derived from Office for National Statistics and National Records of Scotland.

Britain-level percentages of total population or households (derived from grids) and Townsend scores. Scores are given for cells with >0.5 persons or households for all variables for the specific Census year.

-- data not available.

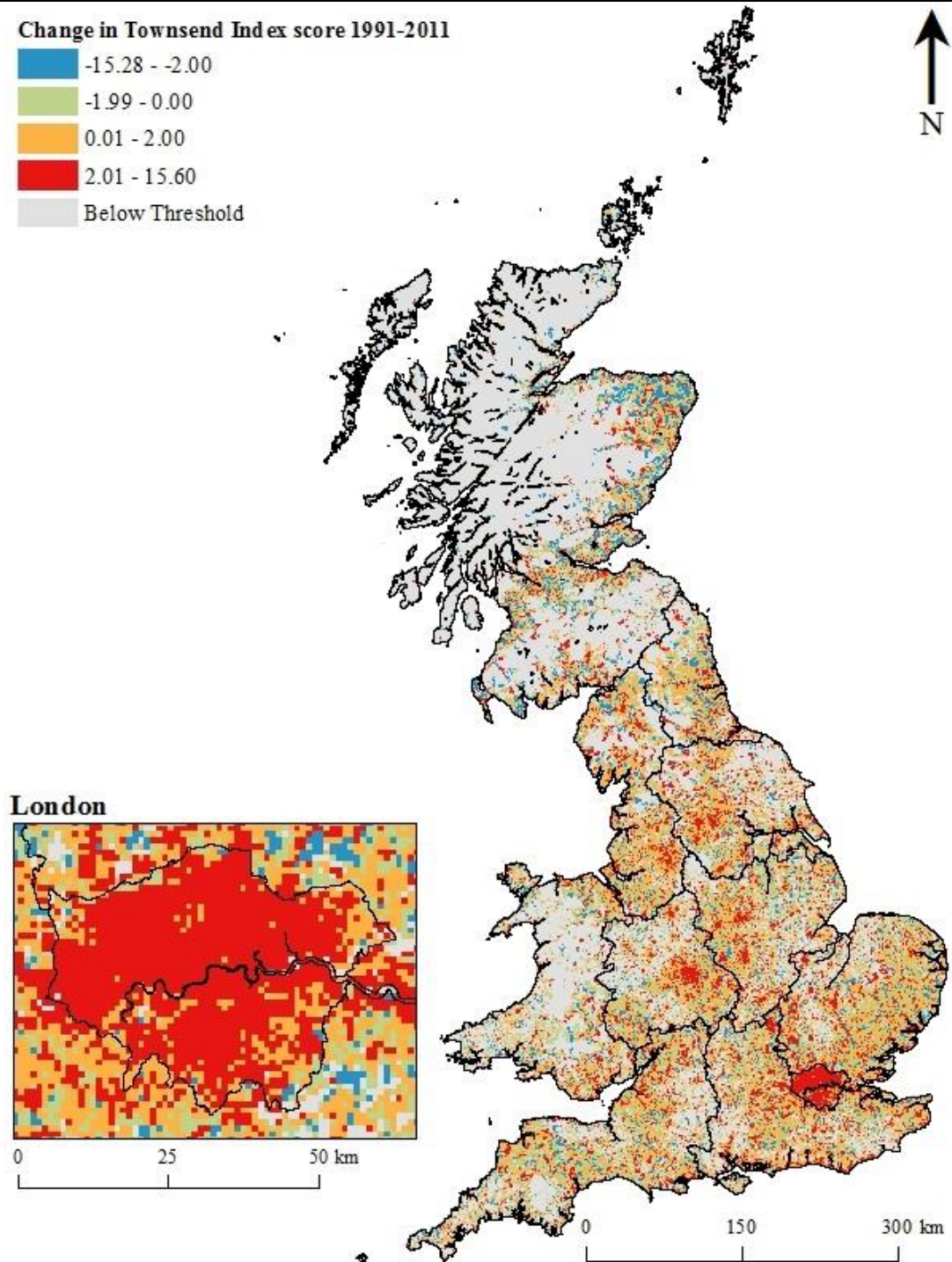


Figure 4.1 Townsend Index score change 1991-2011

Scores are given for cells consistently populated with >0.5 persons or households across all Census years (1991-2011).

Authors calculations using PopChange data derived from Office for National Statistics and National Records of Scotland.

4.3.2 Multivariate regression

The regression coefficient estimates for OLS and spatially lagged models at each time point are reported in Table 4.2. When the components of the Townsend Index are included individually in the models, a greater understanding of the interconnectedness of LLTI and deprivation was achieved. Increased R^2 values were obtained in comparison to those models that alternatively included a composite Townsend score. The R^2 values for all three study periods demonstrate that the model fit improved when a spatially lagged dependent variable was incorporated. Incorporation of a spatial lag element results in around 80% of the variation explained in comparison to 57% or less in each of the models that do not include a spatial element. This suggests that use of spatial regression approaches is beneficial. The decrease in AIC for the spatial lag model relative to OLS suggests that the spatial lag model is beneficial, with the smallest AIC value across all study time points reported for the spatial lag model. Constituent variables were deliberately chosen for their association to the subject matter under study, however, variance inflation factors (VIFs) did not exceed the threshold of 10. Therefore, there is no indication that multicollinearity biased the results (Belsley et al., 2004).

Table 4.2 Regression (Ordinary Least Squares and Spatially Lagged) Coefficients for Limiting Long Term Illness rates in 1991, 2001 and 2011

		1991		2001		2011	
		OLS	SLQC	OLS	SLQC	OLS	SLQC
Model 2a (Townsend Composite Score)	CONSTANT	9.83*	2.58*	15.74*	3.28*	15.78*	3.22*
	Townsend Score	0.57*	0.30*	0.77*	0.39*	0.88*	0.47*
	Age 65+	0.25*	0.13*	0.45*	0.27*	0.43*	0.27*
	Aged 0-14	-0.11*	-0.07*	-0.18*	-0.08*	-0.18*	-0.08*
	Regression						
	Not-UK born	-1.57*	-0.46*	-2.44*	0.83*	-2.77*	-1.00*
	Not White	0.68*	0.02*	0.54*	0.13*	0.25*	0.05*
	ρ		0.73*		0.69*		0.66*
	R^2	0.45	0.78	0.52	0.80	0.55	0.77
	AIC	617,187	519,471	698,151	605,212	685,644	603,440
Model Fit	log-likelihood	-308,588	-259,728	-349,070	-302,599	-342,816	-301,713
	Schwarz Criterion	617,246	519,539	698,210	605,281	685,702	603,508
Model 2b (Townsend Components)	CONSTANT	6.81*	1.29*	11.81*	1.54*	10.98*	0.90*
	Unemployment	0.95*	0.28*	1.55*	0.53*	1.72*	0.68*
	No Car or Van	0.15*	0.07*	0.19*	0.09*	0.21*	0.11*
	Not Owner- Occupied	-0.01*	0.01*	-0.01*	0.00*	0.01*	0.02*
	Overcrowding	0.01*	0.02*	0.42*	0.24*	0.70*	0.35*
	Age 65+	0.18*	0.10*	0.39*	0.25*	0.40*	0.26*
	Aged 0-14	-0.10*	-0.07*	-0.17*	-0.08*	-0.17*	-0.07*
	Regression						
	Not-UK born	-1.11*	0.35*	-1.94*	-0.73*	-2.29*	-0.88*
	Not White	-0.16*	0.26*	-0.07*	-0.05*	-0.25*	-0.13*
Model Fit	ρ		0.69*		0.67*		0.65*
	R^2	0.53	0.79	0.56	0.80	0.57	0.79
	AIC	597,607	511,986	688,614	602,637	677,323	599,784
	log-likelihood	-298,794	-255,983	-344,298	-301,308	-338,653	-299,882
	Schwarz Criterion	597,694	512,084	688,701	602,734	677,411	599,881

Authors calculations using PopChange data derived from Office for National Statistics and National Records of Scotland.

* = p -value < 0.0001, OLS = Ordinary Least Squares, SLQC = Spatially Lagged Queen's Contiguity, ρ = spatial lag term

A reduction in LLTI prevalence, associated with increased numbers of people born outside of the United Kingdom (UK), is reported consistently over all models and is shown to have increased in strength across time. The better health of this group relative to the UK-born is likely to be associated with the ‘healthy migrant effect’; the positive selection of migrants in terms of health (Wallace and Kulu, 2014). As might be expected, Table 4.2 reveals a strong association between LLTI and age and the effect size of both included age coefficients is broadly constant over time. A positive relationship is observed between LLTI and percentage of residents ‘Age 65+’ with a 0.43% increase in LLTI per one unit increase in the proportion of older residents reported for 2011 (OLS model) and similar in previous years. In contrast, an increase in the number of 0-14 year olds is associated with decreasing LLTI rates. The direction of the coefficient estimates regarding age groups are expected given well-established research on the association of morbidity and older age (Gould, 2009).

With regards to the Townsend Index inputs, unemployment is shown to matter significantly for health, with reduced employment levels linked to an increase in prevalence of LLTI. Furthermore, unemployment is shown to have increased in effect size over time. The work of Cooper et al. (2015) suggests that individuals who experience unemployment for more than a short period of time have an increased risk of adverse health outcomes. Overcrowding is negatively associated with LLTI in 1991, but positively associated in 2001 and 2011. The areas with the largest increases in overcrowding between 1991 and 2001, and between 2001 and 2011 have large non-White ethnic populations, and also large numbers of people born outside of the UK – both of which have younger age profiles than those who are White and also UK-born. Ethnic group and country of birth are controlled for in the model which suggests LLTI is positively associated with overcrowding for some ethnic groups (and for some national origins), but not for others.

4.3.3 Residuals

The improved model fit when a spatially-lagged variable is incorporated suggests that the spatial dimension is an inherently important aspect of the relationship between LLTI prevalence and deprivation. Variables included in the model are likely to have highly localised impacts, which cannot be specified in a global model. The residuals from the global regression have been explored to enable the identification of areas where the global model fails to explain a large proportion of the variation. Figure 4.2 displays the mapped residual values from 2011 LLTI global regression (Model 2b).

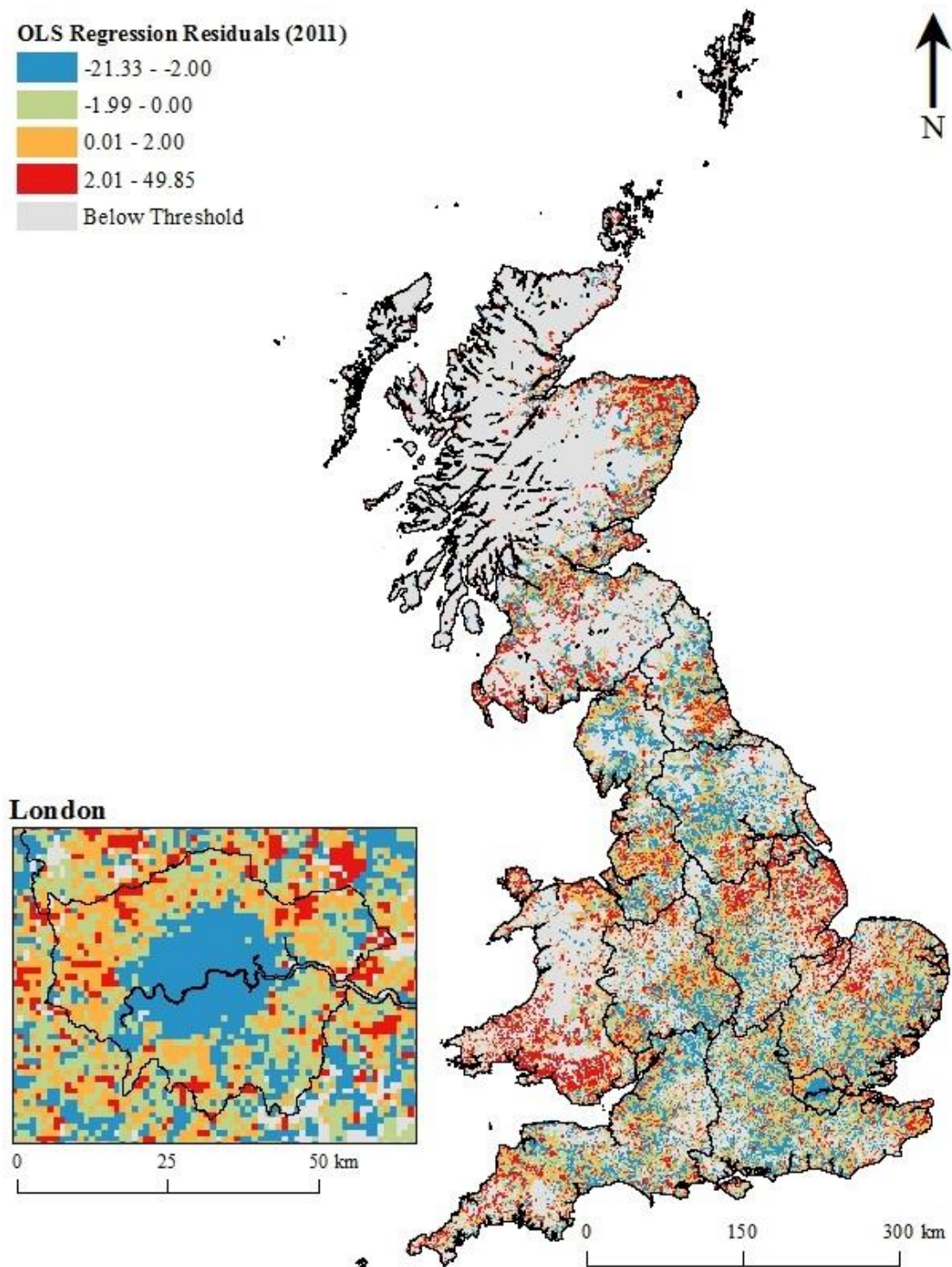


Figure 4.2 Mapped residuals from Ordinary Least Squares (OLS) regression (2011) (population threshold of 0.5 persons)

Authors calculations using PopChange data derived from Office for National Statistics and National Records of Scotland.

The spatial patterning displayed in Figure 4.2 demonstrates the complexity of the relationship between LLTI prevalence and deprivation. It is clear that a global model fails to adequately assess how modelled relations vary spatially. The model fits very well in some areas of Britain but explains substantially less of the variance of poor health in others. Figure 4.2 highlights key localities where large over (less than -2) and under (greater than 2) predictions are distributed across the study area. Exploring the socioeconomic context and composition of areas with particularly high or low residual values can provide valuable information for understanding the localised relationship between deprivation and health inequalities explicitly. Former industrial centres of northern England including Newcastle upon Tyne, Middlesbrough, Sunderland, Sheffield and Liverpool display large under predictions, indicating that the model does not explain LLTI rates well in these areas. Similarly, mill towns in Lancashire and Yorkshire also display larger residual values. Figure 4.2 also reveals large residual values across much of Scotland and in former coal-mining areas, especially in south Wales and north east England as well as in formerly thriving coastal hubs including Grimsby, Morecambe and Rhyl. Areas where the model reports residual values which over-predict LLTI outcomes are predominantly large rural areas; Cumbria, parts of north Wales, Devon and Cornwall, and areas of Northumberland. This could be the result of scale effects as these are large areas which have large input zones, which may be heterogeneous and could indicate that the model is more generalised in areas with low population densities. Although this problem might be solved by introducing interactions in terms of contextual covariates, it is unlikely that all contextual factors can be identified or utilised as operational variables in ecological studies.

The *I* coefficient developed by Moran (1950) has been implemented to provide an indication of the degree of spatial concentration in the residual values from the OLS regression model (2011). The Moran's *I* coefficient value generated was 0.70 and statistically significant ($p < 0.001$). It indicates a strong degree of positive association; small areas with similar residual values tend to occur next to each other. This further confirms spatial variation in the variables that explain the presence of poor health across Britain. The Moran's *I* coefficient value for the same year reduced markedly ($I = 0.21$) when generated for the residuals of the spatial lag model, indicating that much of the underlying spatial structure in the relationship is accounted for.

Figure 4.2 displays the spatial lag model residuals (2011 model). Less apparent spatial patterning in the model residuals is evident, however, some clear spatial structure remains. Former industrial centres, particularly those with a mining heritage including south Wales, Flintshire and Durham, continue to report large under predictions. It is also evident that London remains heterogeneous with small residual values in central London and larger values on the outskirts. Within London area characteristics are likely to change rapidly across space, therefore a different model may be required to fully explain health inequalities. One possibility would be a local regression model which would help unpick the spatial patterning specifically in London and hint at additional variables which could be included in an expanded model.

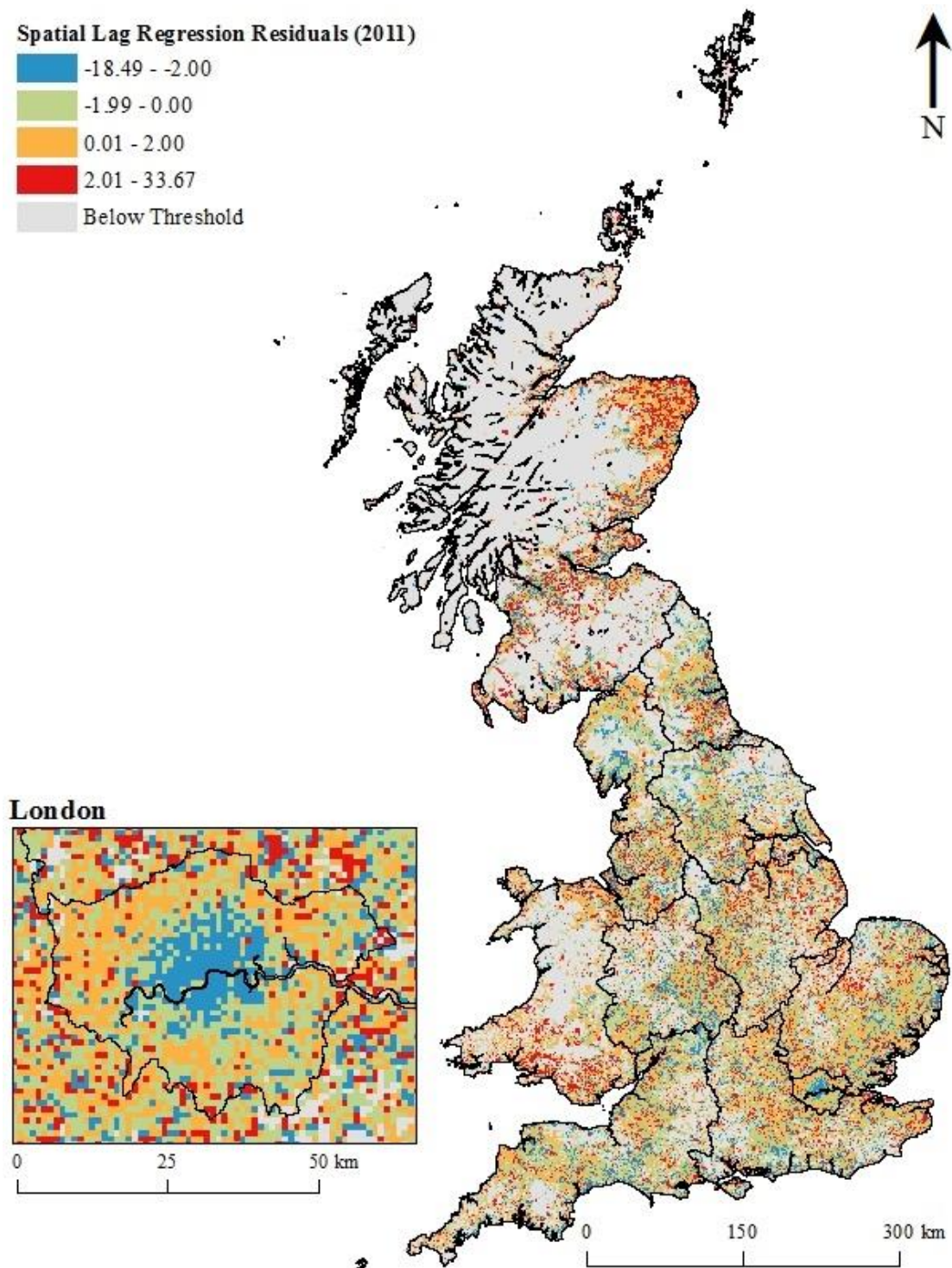


Figure 4.3 Mapped residuals from spatially lagged regression – Queen’s Contiguity (2011) (population threshold of 0.5 persons)

Authors calculations using PopChange data derived from Office for National Statistics and National Records of Scotland.

4.3.4 Exploring change over time

The long-term patterning of small-area deprivation and its association to health patterning are next investigated. Variables were again selected using an iterative stepwise selection process and analysis was repeated including the components of the Townsend Index separately and then as a composite score. Results are presented in Table 4.3. The VIFs did not exceed the threshold of 10; providing no indication that multicollinearity is biasing the results (Belsley et al., 2004). Model fit improved when using the four constituent components of the Townsend Index rather than the composite score. When lag effects through both space (as represented by ρ) and time (achieved through the use of consistent data and inclusion of variables from previous time points) were incorporated the model fit also improved.

Table 4.3 Regression (Ordinary Least Squares [OLS] and Spatially Lagged Queens Contiguity [SLQC]) Coefficients for Limiting Long Term Illness (LLTI) rates in 1991, 2001 and 2011

Variable (%)	OLS	SLQC
1991 LLTI		
No Car or Van 1991	0.15*	0.08*
Age 65+ 1991	0.18*	0.11*
Not-UK born 1991	-1.18*	-0.48*
Unemployment 1981	0.41*	0.13*
Aged 0-14 1991	-0.10*	0.06*
Overcrowding change 1981-1991	0.06*	-0.01*
Unemployment change 1981-1991	-0.07*	0.02*
ρ		0.69*
2001 LLTI		
Age 65+ 2001	0.46*	0.26*
No Car or Van 2001	0.15*	0.10*
Not-UK born 2001	-1.95*	-0.72*
Unemployment 1991	1.25*	0.32*
Unemployment change 1981-2001	-0.14*	-0.03*
Aged 14 and under change 1991-2001	-0.12*	-0.06*
Age 65+ change 1991-2001	-0.02*	0.03*
ρ		0.67*
2011 LLTI		
Age65+ 2011	0.48*	0.29*
No Car or Van 2011	0.18*	0.11*
Not-UK born 2011	-2.26*	-0.87*
Unemployment 2001	2.76*	1.08*
Unemployment change 2001-2011	1.42*	0.60*
Aged 14 and under change 2001-2011	-0.12*	-0.07*
Age 65+ change 2001-2011	-0.11*	-0.06*
ρ		0.64*

Authors calculations using PopChange data derived from Office for National Statistics and National Records of Scotland.

ρ = Spatial Lag Term

The underlying demography of areas was important at each time point. Rates of being born outside of the UK were associated with LLTI prevalence at each time period. This is an effect which appears to have a strong spatial association and has strengthened over time as the percentage of Not-UK born residents within Britain has increased. The age structure was also important. The percentage of young individuals (aged 14 or younger) was consistently negatively associated with LLTI reflecting that most chronic conditions are unlikely in younger populations (Chandola et al., 2007; ONS, 2014). However, contradictory associations were also observed in older populations (other than in 1991). The overall percentage of older populations was positively associated to LLTI rates, however changes between periods were negatively associated, suggesting that larger increases in older populations improved health in small areas.

Unemployment rates at the previous Census time point are consistently reported to explain more LLTI prevalence than unemployment rates pertaining to the Census year under investigation. The effect size of unemployment is especially pronounced when a spatial lag is incorporated, indicating that localised economic factors are important for health. This is further highlighted by the persistent inclusion of unemployment change in the models. The length of time between the Census year of focus and the year which unemployment (or change in unemployment) relates to, the strength of the coefficient and the direction of the relationship between LLTI and unemployment change (%) are period-specific. Across the study period the unemployment rate rose sharply between 1971 (4.08%) and 1981 (10.9%) then fell until 2001. Consequently, when change in unemployment rate is positive this is associated positively with LLTI rate, and when unemployment change is negative, this has a negative association with LLTI. This relationship is most obvious in 2001 when unemployment in Britain had decreased by 5.16% from its 1981 high. This change variable (unemployment change 1981-2001) had a greater effect on LLTI rates in 2001 than change in unemployment only over the 1991 to 2001 period. Between 2001 and 2011 unemployment rates increased by 1.33% and this is associated with an increase in LLTI rates.

For other constituent components of Townsend, only overcrowding did not exhibit consistent associations over the study period. No car or van was positively associated with LLTI. The effect size remained fairly consistent over each time point despite large increases in ownership from 50% in 1971 to 75% by 2011. Results demonstrate that at all time points the size of the effect of 'Not Owner Occupied' was small.

4.4 Discussion

The work presented here is one of the most detailed investigations of small area change of inequalities in health relating to changing deprivation histories for Britain. Using novel gridded population data for 1971 to 2011, it has been possible to unpick the relative contributions of unemployment, no car or van ownership, non-home ownership and overcrowding. Results show that when lag effects through both space and time are considered, deprivation and demographic characteristics explain a large proportion of LLTI variation. This has allowed greater understanding of the relationship between health and deprivation, as well as an exploration of how these associations have varied across space and time. Results demonstrate consistent evidence across all models that small area deprivation, as measured through multiple materialistic dimensions, is positively associated with poor health. Material position and its effect over the life course of place plays a key role in determining health outcomes, with cumulative effects of deprivation known to produce poorer outcomes (Cummins et al., 2007). The role of neighbourhood deprivation was demonstrated to interact with an area's local spatial and historical context. Several cities and regions contained worse health than the model predicted. Departures at a local level suggest specific deprivation histories are important and require further investigation. Materially deprived groups and individuals have been shown to disproportionately experience poor social circumstances (Macintyre et al., 1993). Rosenberg (2014) suggests that the systematic unequal distribution of power, prestige and resources among groups in society operates to exclude certain groups from the material living and working conditions, opportunities for consumption of health promoting goods and services, and chances of social participation that can contribute positively to well-being. The inequalities that exist in the distribution of income, employment, skills, education and housing are systematically associated with social disadvantage and marginalisation (Macintyre, 2007; Marmot, 2010; WHO, 2010).

Given that unemployment as a whole has fallen in Britain over the study period, an increased influence of being unemployed on LLTI prevalence is reported over the same period. The enduring effect of historical unemployment rates are also observed. The lasting effects of deindustrialisation have produced regionally concentrated falls in the demand for labour, most notably in northwest and northeast England and south Wales (Mactaggart et al., 2016). Localised economic and social factors may act over time to particularly amplify the effects of unemployment in the production of local rates of LLTI. High levels of socioeconomic deprivation, underinvestment in human or social infrastructure and services, and limited labour market opportunities contribute to social exclusion, poor health and reduced well-being (Berkman and Glass, 2000; Riva et al., 2011; Mactaggart et al., 2016.) The quality and type of

labour market opportunities is an important consideration for unequal health outcomes. Labour market changes have been accompanied by a decline in the number of full-time and permanent roles and a rise in flexible, precarious employment with limited or no employment or welfare rights (MacInnes et al., 2013). Skill mismatches that result in overall job dissatisfaction can be associated with negative health implications (Mactaggart et al., 2016), especially if the employment does not provide financial resources sufficient to relieve financial pressures (Cooper et al., 2015). This structural inequality has been shown to affect health through disadvantaged material living conditions, discrimination, dominance hierarchies and violence (Berkman and Glass, 2000).

The complex and spatially sensitive relationship observed between poor health and deprivation could also suggest that hidden unemployment has been an important factor in self-reporting of limiting conditions within some areas of Britain (Bambra and Garthwaite, 2015). It has been suggested that the benefits system and the employment services within Britain have diverted people away from unemployment benefits and onto sickness benefits, occurring most prevalently in areas of highest unemployment where jobs are hard to find and occupational ill health is highest (Möller et al., 2013). In a situation of abundant employment opportunities, these ‘hidden unemployed’ individuals could reasonably be expected to participate in the labour market, however, their illness is considered ‘limiting’ when employment opportunities are scarce (Möller et al., 2013). Deindustrialised regions are characterised not only by overall economic decline, but also deteriorating environmental conditions and social disruption (Riva et al., 2011). This has subsequently hindered regeneration and development of new economic pathways. Consequently, such areas are prone to the effects of broader changes in the national labour markets and international economy (Mactaggart et al., 2016).

4.5 Conclusions

This work offers a new level of insight into the changing health and deprivation profiles of small areas in Britain. Comparison of area populations over time allows changes in population health status and progress towards reductions in health inequalities to be assessed. Findings from this investigation have permitted the ‘scene to be set’ for spatial health change and its relationship with deprivation change presenting a fine-grained exploration of changes over time. When lag effects through both space and time are considered, deprivation and demographic characteristics explain a large proportion of LLTI variation. The analysis provides a rich picture of the changing variation of health inequalities in Britain. Results demonstrate that economic inequalities play a significant role in the divergent health profiles of different places and that the long-term socioeconomic history of local areas is especially salient for population health.

The finding that area histories, particularly in relation to employment opportunities, continue to have an important influence on health status, has implications for the ways in which widening health inequalities are approached and how appropriate interventions aimed at reducing inequalities across Britain are applied. Results demonstrate that the extent to which area history is found to matter for health changes through time, with a spatial sensitivity to this relationship implied by the findings. Exploring the spatial patterning of relationships between LLTI and deprivation in further detail through a spatial modelling approach is necessary but was not possible within the confines of this already analysis intensive work. An explicitly spatial approach which incorporates area histories and explores how health at one point in time is influenced by conditions at a previous time point can offer a more complete understanding.

This analysis is the first to explore long-term change in health inequalities and deprivation in Britain at a very fine scale using consistent small area data. The potential for understanding long-term health and deprivation change offered through the use of a comparable Census data set has been highlighted by the novel findings presented here, however, there are some caveats about the results and their interpretation that need to be considered. There are concerns about using aggregate level data to make generalisations about people and places, however, the purpose of this work was to provide a geographically rich analysis that was consistent over time which has been achieved through Census data. The grid cells utilised are small and so generalisations have been minimised. Due to restrictions in availability of comparable variables across time, the analysis uses quite broad categories such as White/non-White. Of course the categories could have been sub-divided and there are likely to have been differences between subsets of the groups used here. As the study is based on Census-derived data, the analysis is restricted to broad 10-year periods and variables that have been recorded in the Census. Whilst the indicators used are believed to be as time-robust as possible, changes to their relevance within society may have occurred over time. Such changes are likely to have been consistent across Britain, however, results should be interpreted with careful consideration of this and in light of wider changes which may have impacted on these variables. For example, the “right to buy” policy instigated by the Conservative government in the 1980s, has been shown to have increased levels of home ownership (Disney and Luo, 2017). Nevertheless, the study holds several considerable advantages and presents important conclusions about how changes in deprivation are associated with changes in LLTI.

4.6 References

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Chapter 5

Exploring spatial variability in changing health inequalities: area deprivation and Limiting Long-Term Illness across Britain in 1991 and 2011

Recognising that places are spatial-temporal products the fifth chapter of this thesis explicitly considers the historical and geographic dimensions of health inequalities, building on the evidence presented in chapters 3 and 4. Extending the contributions made in in chapters 3 and 4 by using explicit spatial methods, this chapter aims to further explore the finding that determinants of health are experienced differently across space. This chapter also explores the long-term geography of health inequalities; identifying how health at one point in time is influenced by conditions at a previous time point. Chapter 5 is based upon a journal paper of the same name currently under review at *Social Science & Medicine*.

5.1 Introduction

As demonstrated in Chapter 3 health has been found to be increasingly spatially organised within Britain leading to more pronounced spatial divisions of long-term illness. A number of demographic and social factors that are associated with poor health outcomes have also experienced similar patterns of increasing spatial segregation within Britain (Catney, 2016; Lymeropoulou and Finney, 2016; Sabater et al., 2017). Social and spatial health polarisation is not inevitable and exploring spatial variation in health inequalities is an imperative policy objective in Britain (Public Health England [PHE], 2015). A more nuanced understanding of geographic variation in health and the wider determinants of unequal health outcomes between more and less advantaged populations is imperative to improve population health and eliminate unjust, avoidable and unfair disparities in health across Britain.

Social and economic inequalities are salient determinants of population health, and it is well documented that these protective and risk factors are not evenly distributed across people or places (Macintyre et al., 2002). There is an extensive literature documenting pervasive and

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persistent socioeconomic gradients in health that manifest geographically (Acheson, 1998; Macintyre et al., 2005; Marmot, 2010, Whitehead, 2014). Areas within Britain have population compositions, contextual area characteristics, and differing opportunity structures in the physical and social environment that make them distinct from other locales and contribute to the existence of geographic health inequalities (Macintyre et al., 1993; Marmot, 2010). People and their health shape, and are shaped by, the places in which they live and inhabit on a regular basis (Bambra et al., 2019). This is in part because people with similar sociodemographic characteristics tend to cluster in space, and in part because individuals living in the same neighbourhood are subject to common contextual influences (Boyle et al., 2004; Smith and Easterlow, 2005). Some local areas have lower unemployment rates than others (Rae et al., 2016), whilst in some places there is a greater mix of ethnic groups than elsewhere (Catney, 2016), and research suggests increasing spatial age segregation within the United Kingdom (UK) (Sabater et al., 2017).

Sridharan et al. (2007) using Scottish data found that mortality in postcode sectors was significantly higher in those sectors which had high levels of deprivation in the proximate sectors, demonstrating that spatial patterns of deprivation, rather than just levels of deprivation, might be implicated in explaining variations in health. Additionally, the life-course of place and durability of characteristics can function to pattern and shape health disparities in space and over time (Pearce, 2015; Lekkas et al., 2017; Pearce et al., 2018). Using an ecological analysis Dorling et al. (2000) found that mortality attributable to diseases such as lung cancer and stroke in 1991 was predicated more strongly by the spatial distribution of a historic 1896 measure of poverty more than a contemporary expression of this exposure. Greater investigation into how experiences of place-based inequality manifest themselves in health, not only at a single point but over time, is key to illuminating the processes through which spatial inequalities are being maintained and how they might be successfully reversed.

Underpinning geographic thinking is the assumption that spatial phenomena vary across a landscape (Tobler, 1970). Space is continuous and neighbouring geographies are likely to share similar compositional and contextual characteristics that are spatially correlated (Anselin et al., 2006; Caughy et al., 2007). More specifically, a set of conditions in one area may affect health outcomes in neighbouring areas (Tobler, 1970). To date, much geographically-focused health inequalities research has relied on conventional non-spatial methodologies. Ignoring the spatial dependencies between variables may result in biased estimates, misleading conclusions and consequently, ineffective interventions (Anselin, 1996). Understanding the complex spatial structuring of health is important, especially for addressing health inequalities and for assessing

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the most appropriate scale at which to introduce interventions designed to improve health and well-being and create a more equal society.

Over the last two decades the local-based regression technique Geographically Weighted Regression (GWR) has gained popularity for exploring spatial non-stationarity. At its most fundamental, GWR is an exploratory technique that can facilitate the identification of areas with high rates of poor health and help better understand which predictors are associated with health outcomes at specific locations. GWR corrects for spatial heterogeneity and dependence by estimating local parameters that capture the distinctiveness of place and emphasise the spatial patterning of relationships (Fotheringham et al., 2002). As such, it can estimate how associations vary spatially rather than assuming relationships to be consistent across multiple contexts. Few studies have employed GWR techniques to examine contextual influences on health inequalities at any aggregate level, however there are notable exceptions, particularly in the obesity literature (Black, 2014). Utilising GWR to explore non-stationarity in the relationship between obesity and selected covariates at county-level in the United States (US) using a rich dataset of demographic, socioeconomic and environmental variables constructed from several secondary sources. Black (2014) established that place matters for health in terms of obesity prevalence, finding the relationship between obesity prevalence and ecological influences varies substantially across place. Lankila et al. (2013) employed GWR using a gridded population to explore non-stationarity in the association between health and migration in northern Finland. Consequently, GWR provides a useful basis to design interventions that successfully target health inequalities at a fine-grained, local level.

5.2 Methodology

5.2.1 Data

Census data allocated to consistent 1km² grid cells for Britain for 1971, 1981, 1991, 2001 and 2011 is utilised in this investigation. The gridded data were generated as a part of the PopChange project (for more information see Lloyd et al., 2016 and Lloyd et al., 2017a) by overlaying source zones (Enumeration Districts [EDs] or Output Areas [OAs]) with 1km² grids, using postcode densities to allocate parts of the populations of source zones to grid cells. Using consistent gridded cells to analyse local-level changes removes complications caused by inconsistencies in the geographies used to report counts which can hinder analysis of change over time at a fine spatial scale (Norman, 2010). Allowing for comparison across time, and arguably providing a more natural representation of population distribution across Britain, analysis was conducted only on grid cells which were estimated to be consistently populated at a population threshold of 25 persons through all five Census time points.

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Health inequality is measured by the proportion of people reporting a Limiting Long-Term Illness (LLTI). LLTI is a commonly used measure of self-reported health and was first included in the Census of England and Wales, and Scotland in 1991. Census-based health measures are important indicators of morbidity both in individuals and at an area-level, and are widely used to explore the geographies of health (DeSalvo et al., 2005; Jylha, 2009; Wu et al., 2013; Cooper et al., 2015; Putrik et al., 2015). In the most recent Census the measure asked “Are your day-to-day activities limited because of a health problem of disability which has lasted, or is expected to last, at least 12 months? Include problems related to old age” (Office for National Statistics [ONS], 2013). Based on ONS guidelines, LLTI response options for all Census years were dichotomised into consistent groupings for comparison over time; ‘Limited’ or ‘Not Limited’ (expressed as a percentage of all people) (ONS, 2013). Further detail is provided in Table 3.1.

Variable selection was informed and theoretically justified through previous work. Analysis makes use of Census-derived variables that are available in the ‘PopChange’ resource including population density, age, ethnicity, country of birth and components of the Townsend Index. The Townsend Index is a composite score comprising of percentages of: unemployment, lack of access to a car or van, non-home ownership, and household overcrowding (more than one person per household room) (Townsend, 1979) and has been widely utilised in academic studies and public health reports (Higgs et al., 1998; Lloyd et al., 2017b). Greater understanding of the interconnectedness of health outcomes and deprivation was obtained by unpicking the relative contributions of Townsend Index component variables; an approach which facilitated the identification of the extent to which different factors are important geographically and how this changes through time.

Rates of LLTI measured in 1991 and in 2011 were the variables of interest for this investigation. An approach which incorporates area histories and explores how health at one point in time is influenced by conditions at a previous time point can offer a more complete understanding of health inequalities and their spatial manifestation. A sensible and informed approach to variable selection was made that allows comparability and change of effects over time to be seen. To facilitate comparability across time and identification of how persistent the effects of each variable are, a common subset of explanatory variables was identified for all models. The incorporation of variables relating to previous time points offers a long-term approach to understanding how health inequalities in Britain manifest spatially. For this reason, rates of explanatory variables relating to previous Census periods including (where available) those pertaining to 1971 and 1981 were also incorporated into the models, (for example, a model seeking to explain LLTI in 1991 included unemployment rate recorded at the 1981 Census).

Additionally, to provide further depth to understanding of the relationship between health inequalities and deprivation, changes in variables between consecutive Census years were calculated and included. For example, Unemployment change between 2001 and 2011 = Unemployment rate in 2011 minus Unemployment rate in 2001.

A detailed area classification scheme has been applied to stratify the results, allowing a greater level of geographical understanding to be obtained. Small area grid cells were grouped using the 2011 ONS 2011 Area Classification for Local Authorities (ONS, 2014). The top tier classification comprising eight Supergroups of areas in the United Kingdom is utilised. This classification is based on 59 demographic and socioeconomic variables drawn from the 2011 Census and has been used extensively in academic research (for example, Lymperopoulou and Finney, 2016) to provide descriptive characterisations of geographic areas. It should be noted that this classification covers the whole of the UK but in the present study has been applied only to Britain, therefore the ONS classification of ‘Scottish and Northern Irish Countryside’ applies only to Scotland and will, hereafter, be referred to as ‘Scottish Countryside’. A map displaying the 1km² grid cells meeting a population threshold of 0.5 persons and classified by area type can be seen in Chapter 3 (Figure 3.3, page 80). For further information regarding the data sources utilised in this thesis, please refer to Appendix D, page 184,

5.2.2 Geographically Weighted Regression

In recognising that the relationship between deprivation and health may not be spatially constant, an assessment of how modelled relations vary spatially is achieved through the use of Geographically Weighted Regression (GWR) techniques that expand standard regression for spatial data by allowing for spatial variance in the estimated parameters. Places closer together in space are expected to be more similar than places further apart (Lloyd, 2010). This approach facilitates a comprehensive assessment of how geography matters for health; how far the nature of the relationship between poor health prevalence and contextual variables varies spatially at a small-area level, and how strongly predictors are associated at specific locations.

GWR considers spatial heterogeneity and spatial dependence of data by estimating local, more robust, parameters that capture the distinctiveness of place and the spatial variations between dependent and independent variables (Brunsdon et al., 1998). GWR constructs a separate regression equation for each observation (grid cell). Each equation is calibrated using a different weighting of observations contained in the dataset. The GWR model can be expressed as follows:

$$y_i = \beta_0(u_i, v_i) + \sum_k \beta_k(u_i, v_i) \chi_{ik} + \varepsilon_i \quad [6]$$

Chapter 5: Exploring spatial variability in health inequalities across Britain in 1991 and 2011
where (u_i, v_i) denotes the spatial coordinates of the i^{th} point in space and $\beta_k(u_i, v_i)$ is parameter estimate at location i . This spatially explicit approach allows the identification of relationships that are likely masked using traditional regression methods, where it is assumed that the relationship between variables are the same throughout the entire study area. The underlying assumption of the global regression method is that the relationship under study is spatially constant. When exploring spatially complex concepts using regression models it is often unreasonable to assume a single set of regression coefficients can capture space-varying and scale-dependent relationships between covariates and the outcome variable. A standard Ordinary Least Squares (OLS) regression is also calculated to explore how the model improved when a spatially explicit geographically weighted approach is taken.

When GWR is applied, key decisions concern the choice of a weighting function and the bandwidth of the kernel (Brunsdon et al., 1998). Each grid cell centroid is a regression calibration location and parameter estimates are made using a spatial proximity approach in which observations in closer proximity receive larger weights than observations further away (Lloyd, 2010). Hence neighbouring cells have more influence than more distant ones (Brunsdon et al., 1998). A fixed bandwidth of 60 nearest neighbours was selected. ArcMap10.6™ was used to implement GWR and map the resulting coefficient estimates.

For each grid cell in the dataset standardised coefficients from each GWR model were ranked according to the coefficient that had the largest effect in that cell. This approach allowed the identification of spatial patterning in the factors that matter most for health outcomes by location. Additionally, these results were stratified by area classification type and subsequently mapped, providing a useful way of summarising the complex information contained in the GWR model outputs.

5.3 Results

A common subset of explanatory variables was identified for all models which comprised of a combination of: variables from the Census year under consideration; those relating to the previous Census year; and those which represented a change between the year under consideration and the previous Census year. A longer time-lag, extending beyond only the Census prior to the year of investigation was also considered, however, testing showed these longer-term relationships to be less revealing. The model used includes the percentage scores of; ‘Unemployment’ (Census year of study), ‘Unemployment’ (relating to the Census conducted ten years prior to the year of study), ‘Age 65+’ (Census year of study), ‘Change in Age 65+’ (from previous Census to study year), ‘Change in car ownership’ (from previous Census to study year) and ‘Not-UK born’ (Census year of study). Descriptive statistics are provided in Table

5.1. Median rate of LLTI has increased from 10.43% in 1991 to 17.41% in 2011. Disaggregating results by area classification type demonstrates variability in LLTI (Table 5.4 *Appendix B*). The highest median LLTI value is observed in ‘Mining Heritage and Manufacturing’ area type (20.19%), followed by ‘Coast and Heritage’ (19.18%). Lowest median rates are in ‘London Cosmopolitan’ (13.69%) and ‘Prosperous England’ (13.88%). Changes in LLTI between 1991 and 2011 were also not consistent across Britain with larger increases observed in ‘Coast and Heritage’ and ‘Scottish Countryside’ and the smallest increases in ‘London Cosmopolitan’ and ‘Prosperous England’

Table 5.1 Descriptive Statistics for Britain

	1991			2011		
	Median	Minimum	Maximum	Median	Minimum	Maximum
LLTI	10.43	0.03	34.58	17.41	1.40	58.53
Unemployment	1.90	0.00	4.02	1.62	0.00	3.61
Unemployment (previous Census)	2.01	0.00	4.38	1.47	0.00	3.53
Age 65+	15.96	0.00	78.62	19.60	0.02	77.09
Change in Age 65+ (from previous Census to study year)	1.04	-68.52	63.92	2.70	-32.33	35.56
Change in car ownership (from previous Census to study year)	-5.61	-72.75	60.11	-1.59	-67.70	58.78
Not-UK-born	1.40	0.00	4.50	1.75	0.00	4.47

Authors calculations using PopChange data derived from Office for National Statistics and National Records of Scotland.

Table 5.2 Global regression model summaries 1991 and 2011 (*N*= 53526)

		1991		2011	
		Coefficients	Confidence Intervals 95 Level (%) (Lower bound, upper bound)	Coefficients	Confidence Intervals 95 Level (%) (Lower bound, upper bound)
Variables	(Constant)	-0.853	(-0.983, -0.722)	1.431	(1.248, 1.614)
	Unemployment	2.643*	(2.587, 2.700)	0.498*	(4.171, 4.315)
	Unemployment (previous Census)	2.019*	(1.964, 2.073)	4.243*	(2.594, 2.722)
	Age 65+	0.288*	(0.285, 0.292)	2.658*	(0.493, 0.502)
	Change in Age 65+ (from previous Census to study year)	-0.001*	(-0.001, -0.001)	-2.144*	(-0.178, -0.163)
	Change in car ownership (from previous Census to study year)	0.018*	(0.016, 0.020)	-0.171*	(0.014, 0.020)
	Not-UK born	-1.479*	(-1.516, -1.443)	0.017*	(-2.109, -2.098)
Model Fit	<i>R</i> ²	0.616		0.668	
	AIC	243,405		270,074	
	log-likelihood	-121,696		-135,030	
	Schwarz Criterion	243,468		270,136	

*Authors calculations using PopChange data derived from Office for National Statistics and National Records of Scotland., * = *p*-value <0.0001*

5.3.1 Global model

As outlined in section 5.2.2, OLS regression calculates one parameter estimate for each variable and a single measure of model fit. The global coefficient estimates for OLS models at each time point (1991 and 2011) are reported in Table 5.2. Model fit was good with analyses explaining 61.6% and 66.8% of the observed variance of LLTI across Britain in 1991 and 2011 respectively. In 1991 the percentage of unemployment in an area in that Census year is found to have a large effect on LLTI prevalence. As the percentage of unemployment increased by one unit, the rate of LLTI in that area increases by 2.64%. A positive relationship between unemployment levels in 1981 and LLTI in 1991 is also reported, where a one unit increase in the proportion of unemployment in 1981 increased LLTI recorded in 1991 by 2.02%. In the 2011 model unemployment rates at the current year were found to have a small association with LLTI rates (0.50%) but unemployment at the previous Census year (2001) had a strong positive relationship to LLTI prevalence (4.24%).

At both time periods there is a positive association for ‘Age 65+’; the greater the percentage of older people in an area, the higher LLTI rate is. This is especially prominent in the 2011 model. However, when exploring change, areas that saw increasing percentages of in this age group over time had lower LLTI rates. Change ‘Age 65+ 1981-1991 is much larger than change in this group between 2001 and 2011. The effect on health at a global level of change in car ownership and not UK-born is not consistent across time, with the direction of these values reversing. The direction of these coefficients is likely to reflect substantial changes in the size of these groups that occurred in Britain over the study period, and may have changed the meaning of these variables over time. Further analysis is needed to determine spatial heterogeneity in the outcome variables.

Table 5.3 Geographically Weighted Regression model summaries unstandardised coefficients 1991 and 2011 ($N = 53526$)

	1991			2011		
	Median	Minimum	Maximum	Median	Minimum	Maximum
Local R^2	0.69	0.03	0.97	0.74	0.04	0.98
Unemployment	1.73	-9.06	11.95	2.97	-13.56	18.06
Unemployment (<i>previous Census</i>)	1.07	-7.97	11.46	1.53	-11.95	12.56
Age 65+	0.33	-0.39	0.99	0.53	-0.30	1.50
Change in Age 65+ (<i>from previous Census to study year</i>)	0.00	-0.14	0.16	-0.15	-1.18	1.83
Change in car ownership (<i>previous Census to current study year</i>)	0.03	-0.27	0.36	0.04	-0.39	0.66
Not UK-born	-0.86	-11.98	7.52	-0.91	-12.18	13.00

Authors calculations using PopChange data derived from Office for National Statistics and National Records of Scotland.

5.3.2 Geographically Weighted Regression

Table 5.3 reports GWR model results. The GWR model reports local R^2 values ranging from 0.03-0.97 (1991) and 0.03-0.98 (2011). Comparatively the global OLS regression analysis models reported single r-square values of 0.62 (1991 model) and 0.67 (2011 model). For both time points, the GWR model is a better fit than the unweighted global model and this suggests that taking the distance from the location of interest into account on a local basis is beneficial to understanding the relationship LLTI prevalence and local area characteristics.

The model fits very well in some locations within Britain but explains substantially less of the variance of LLTI in others (Figure 5.1). A pronounced pattern of higher R^2 values in urban, compared to rural locations, is evidenced at both time points. The level of detail achieved through the use of 1km² grid cells allows detailed patterning in the spatiality of the relationship between area deprivation and health to be observed. Specifically, higher R^2 values were reported in different types of urban areas including: former industrial centres such as Newcastle, Sunderland, Leeds, Sheffield, and Liverpool; mill towns of Lancashire and Yorkshire such as Bolton, Oldham and Bradford; and, former coal-mining areas especially in south Wales and north east England. The fine-scale analysis also allows distinctive patterning of high R^2 values in coastal areas such as Grimsby, Skegness and Rhyl to be distinguished. The areas in which the model performs poorly are predominantly large rural areas; Cumbria, north Wales, parts of Devon and Cornwall and areas of Northumberland which lie along the Scottish border. This could indicate that the model is more generalised in areas of Britain with low population density. Table 5.3 also demonstrates that the effect of the covariates varies greatly across the study area. The minimum and maximum values recorded for unemployment covariates especially display noteworthy variation. For reference maps displaying key localities across Britain please see Appendix C (page 182).

The value of a GWR approach provides the first step in seeking to explain why such differences occur through the ability to map coefficients and identify where the model could be improved. The coefficients for all six explanatory variables show distinguished spatial variability in the associations between the sociodemographic context of local areas and health inequalities across Britain. The mapped unemployment variable coefficients in particular display pronounced spatial patterning and can be seen in Figure 5.2.

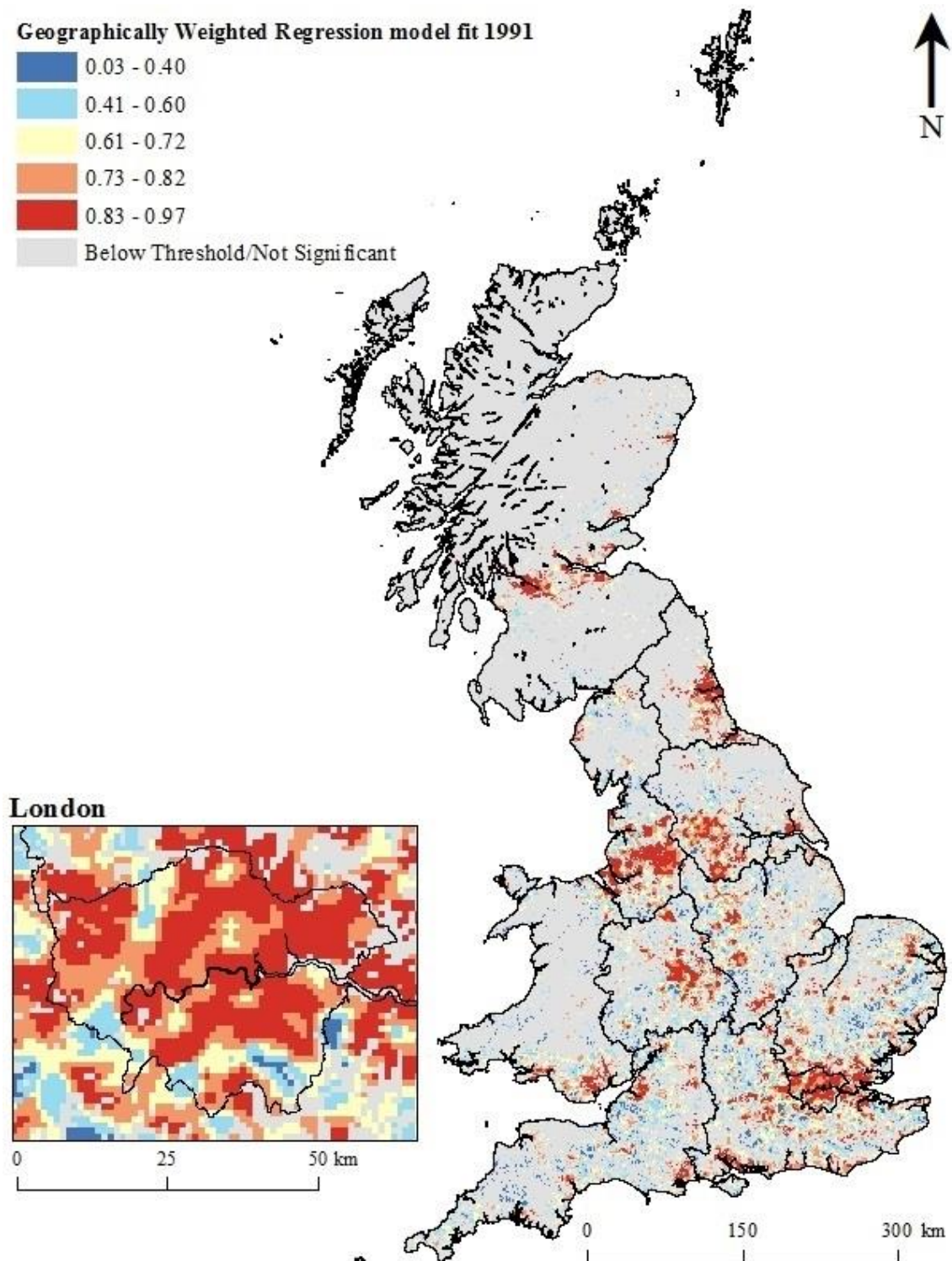


Figure 5.1a (1991) The geographical distribution of model fit (R^2) values from a Geographically Weighted Regression model explaining Limiting Long Term Illness across Britain.

(population threshold of 25 persons)

Authors calculations using PopChange data derived from Office for National Statistics and National Records of Scotland.

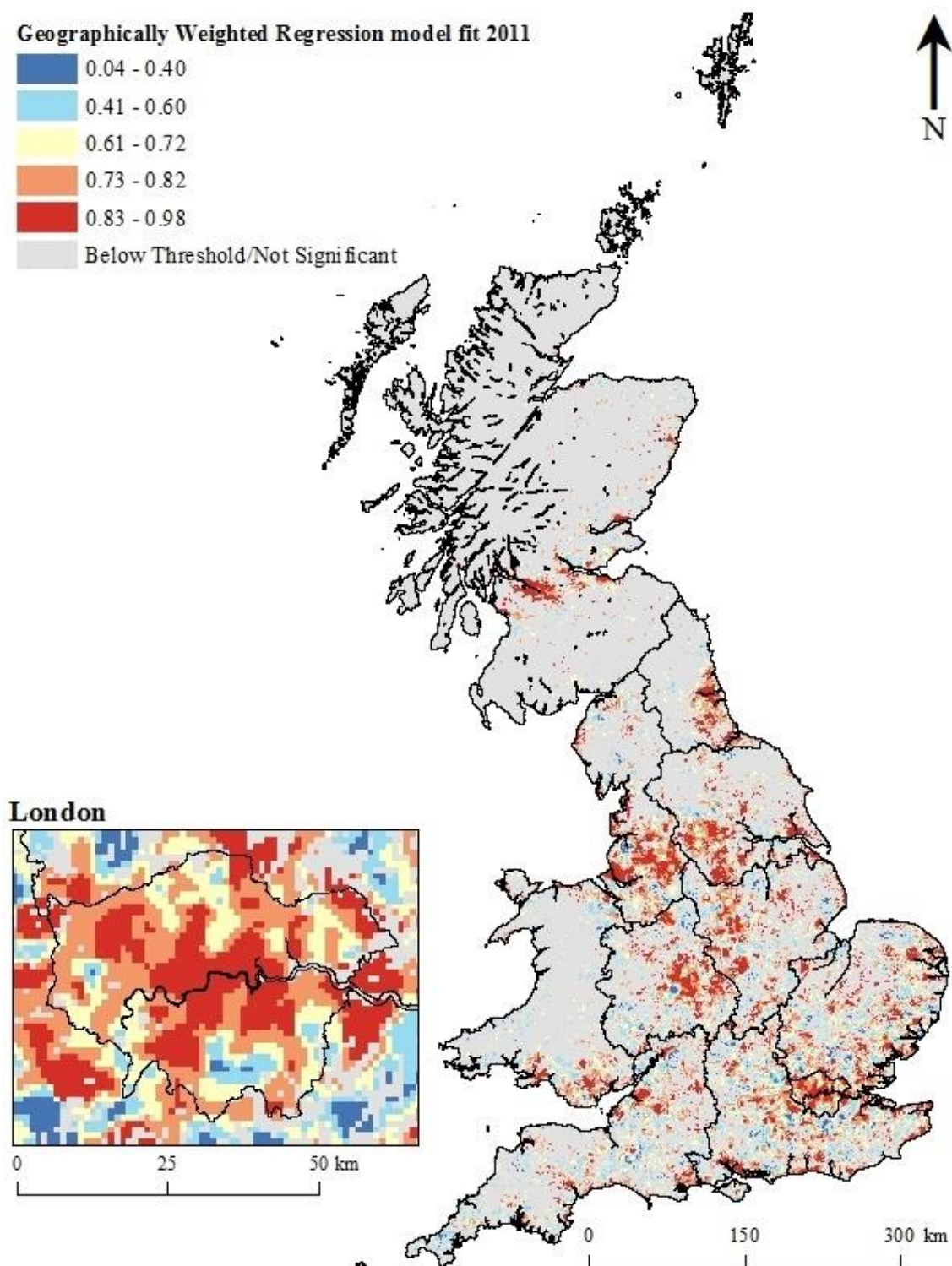


Figure 5.1b (2011) The geographical distribution of model fit (R^2) values from a Geographically Weighted Regression model explaining Limiting Long Term Illness across Britain.

(population threshold of 25 persons)

Authors calculations using PopChange data derived from Office for National Statistics and National Records of Scotland.

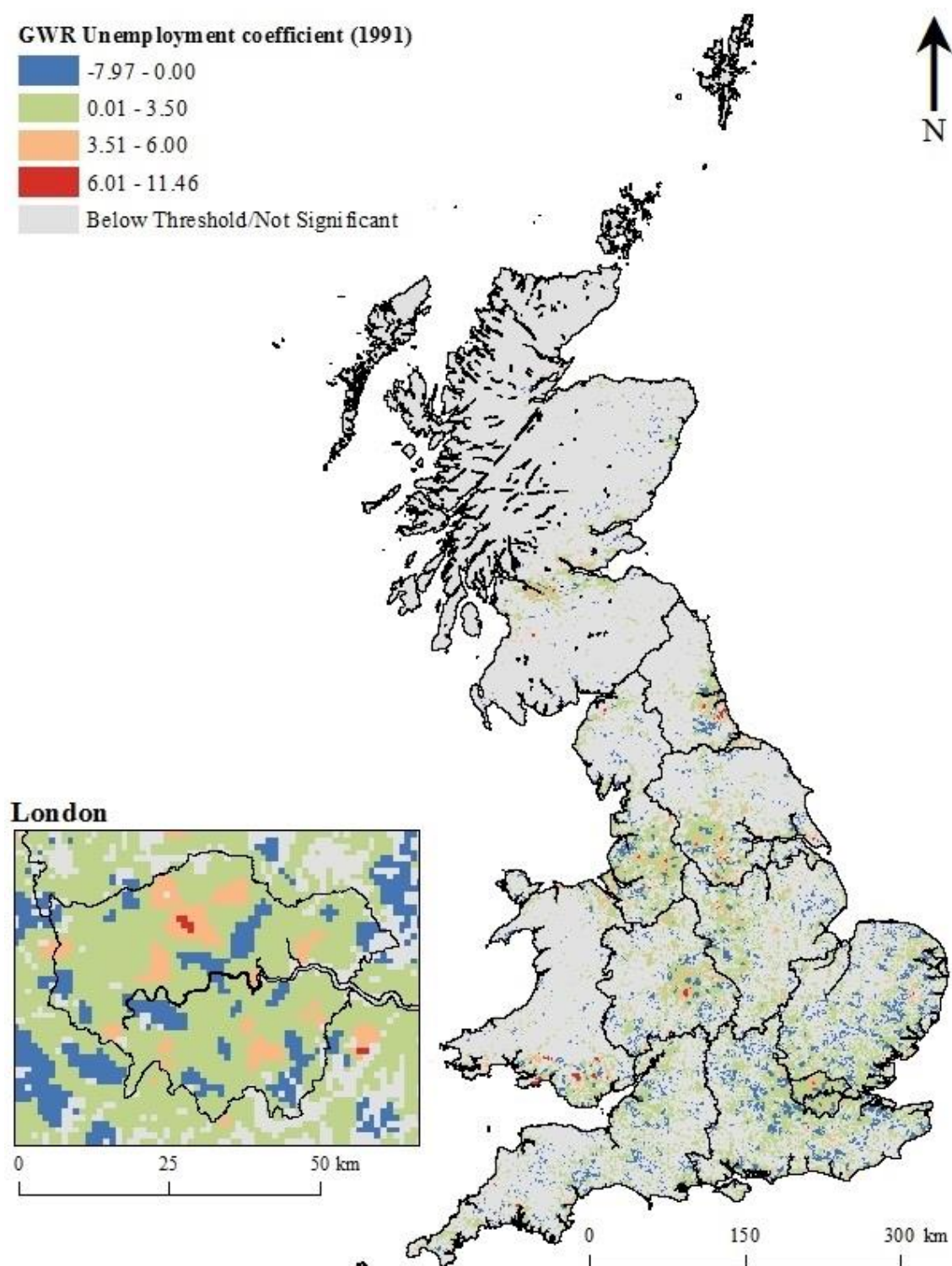


Figure 5.2a (1991) Geographically Weighted Regression (GWR) coefficients for Unemployment (population threshold of 25 persons)

Authors calculations using PopChange data derived from Office for National Statistics and National Records of Scotland.

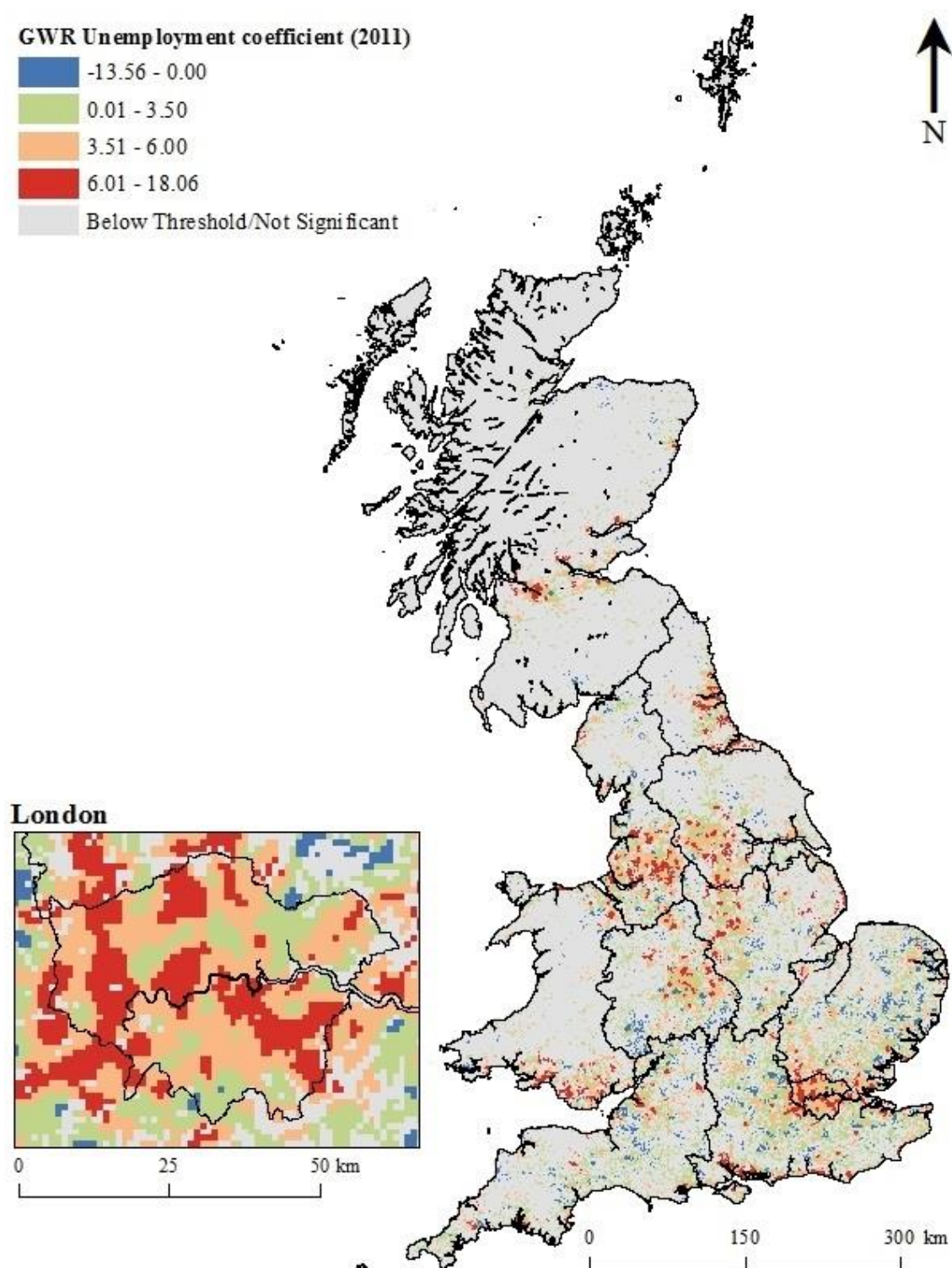


Figure 5.2b (2011) Geographically Weighted Regression (GWR) coefficients for Unemployment (population threshold of 25 persons)

Authors calculations using PopChange data derived from Office for National Statistics and National Records of Scotland.

The mapped unemployment coefficient values displayed reveal clear spatial disparities in the extent to which being unemployed is worse for health (Figure 5.2). Despite decreasing levels of unemployment overall, unemployment in major urban centres has increased and this is a key contributing factor to changing deprivation levels. In areas with a legacy of deindustrialisation such as the coalfields of south Wales and north east England and mill towns in north west England, a strong positive association between LLTI and unemployment is established. In these areas the effect of being unemployed is worse for health (than in areas where the association is smaller or negative). There is also clear spatial patterning of this positive association evident in port ‘settlements’ including Liverpool, Newcastle, Edinburgh, Plymouth, Portsmouth and Southampton as well as in seaside resorts; Weston-Super-Mare, Prestatyn, Ryhl, Southport, Fleetwood, Morecambe, Torquay, Newquay, Brighton, Eastbourne, Southend-on-Sea, Skegness and Clacton-on-Sea. Figure 2 also shows that being unemployed matters more in London compared to some other areas of Britain.

This spatial variance demonstrated supports claims that some areas may be more health promoting than others but that this itself varies geographically. It is clear that coefficients are experienced differently across space with some coefficients more important in certain areas than others. To further explore this the largest standardised coefficient for each grid cell generated from GWR models is displayed in Figure 5.3.

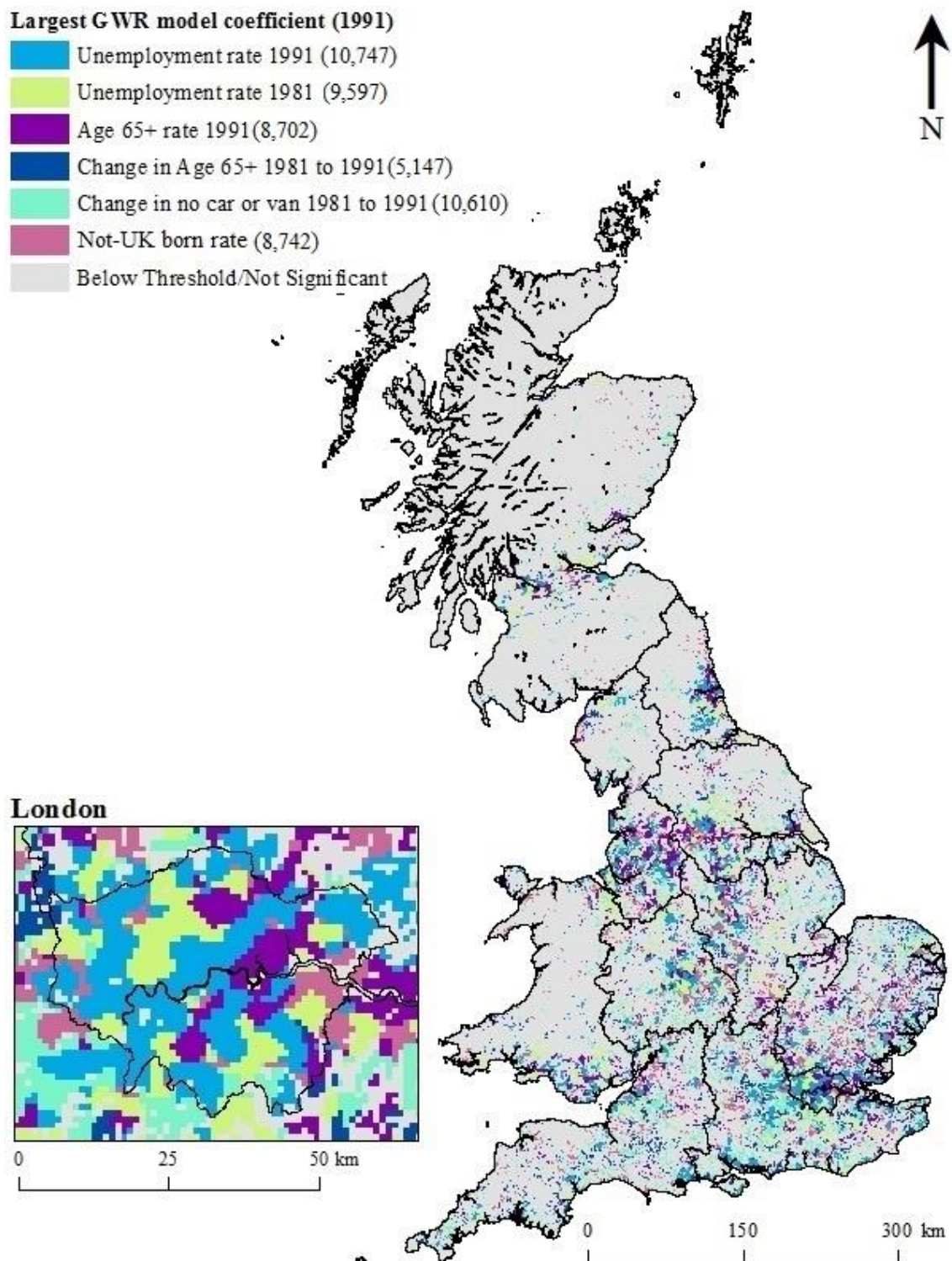


Figure 5.3a (1991) Largest Standardised Coefficient for each grid cell 1 within the 1991 Geographically Weighted Regression (GWR) model (population threshold of 25 persons)

Authors calculations using PopChange data derived from Office for National Statistics and National Records of Scotland.

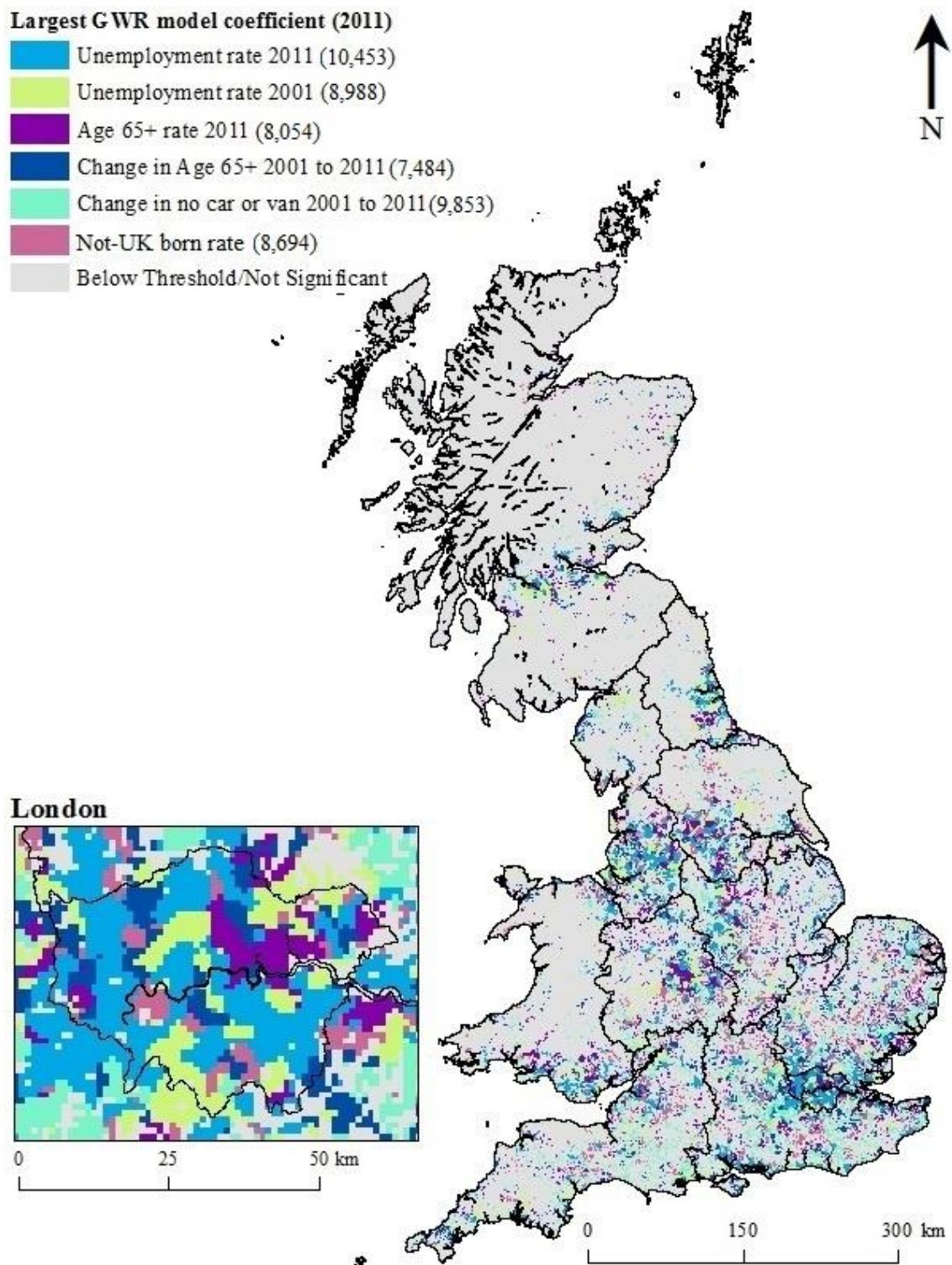


Figure 5.3b (2011) Largest Standardised Coefficient for each grid cell 1 within the 1991 Geographically Weighted Regression (GWR) model (population threshold of 25 persons)

Authors calculations using PopChange data derived from Office for National Statistics and National Records of Scotland.

In terms of the largest standardised coefficients for each grid cell, generally there is considerable continuity from 1991 to 2011. Through exploring which standardised coefficient had the largest effect in each individual cell, it is possible to determine if area effects are experienced equally across space and over time. For example, while unemployment at the current time point was the largest standardised coefficient for most grid cells, results confirm the effect of unemployment is not experienced uniformly across Britain. In urban centres unemployment (or unemployment at the previous Census year) is most frequently recorded as the largest standardised coefficient. In areas with industrial legacies, particularly localities with coal mining and manufacturing histories, unemployment rate at the previous Census year is especially pronounced as important. Legacies of unemployment, rather than unemployment itself appear to be very important. This is seen in Newcastle, Derbyshire, Sheffield, south Wales and Glasgow. There is also very clear patterning of unemployment at the previous Census year being important for many coastal areas including Grimsby, Great Yarmouth and Eastbourne. Additionally, many deindustrialised localities show the percentage of the population 'Age 65+' at the current Census year to be the largest standardised coefficient. This could be because in this age group there will be many individuals who were employed in these industries prior to deindustrialisation, and consequently, who are likely to have suffered the direct physical health effects associated with working in heavy industry.

At both time points it is mainly very rural cells that report the percentage of 'Age 65+' in the current Census year to be the largest standardised coefficient. In more urban localities age is concerned predominantly when it relates to a change in the percentage of 'Age 65+' (previous Census to current Census year). Percentage change in age 65+ is also an important factor in some areas of London. In urban fringe change in car ownership appears to be important, this is especially prominent in a wide band of rural southern England – closely aligned with areas typified as 'Prosperous England'. It is clear from Figure 5.3 that 'Not-UK born' is an important factor in more rural localities than more urban ones, with the exception of some distinctive areas within London.

5.3.3 Stratification by area classification

The GWR output analyses were stratified by area classification supergroup to provide further geographical detail on how coefficients act in different localities (see Table 5.5 (1991) and 5.6 (2011), Appendix B). At both time points, the lowest median unemployment coefficient values are reported in 'English and Welsh Countryside' and 'Prosperous England'. 'London Cosmopolitan' had the largest median coefficient observed. In 'London Cosmopolitan' in 1991, unemployment rate in 1991 was the most important coefficient for 50% of grid cells. A further 19% of cells reported the unemployment rate at the previous Census (1981) to be the most

important coefficient for LLTI. ‘Business and Education Centres’, ‘Mining Heritage and Manufacturing’, and ‘Suburban Traits’ also have high rates across both periods. Across ‘Scottish Countryside’ overall unemployment rate at the 1981 Census was a more important factor for LLTI in 1991 than unemployment rate recorded in the 1991 Census, demonstrating the enduring effects of unemployment on health outcomes.

In 1991, the grid cells which reported change in the percentage of ‘Age 65+’ to be the largest standardised coefficient most frequently were those classified as ‘Coast and Heritage’ and ‘English and Welsh Countryside’. Other area types reported comparatively few cells where this coefficient was the largest. Change in ‘Age 65+’ was not an important coefficient within ‘London Cosmopolitan’ with no grid cells reporting this as the largest standardised coefficient in 1991, however by 2011 17% of cells did. This reflects a trend of increased importance of change in ‘Age 65+’ for all area types over time, but such increase is shown to have been experienced differently by area type. The extent to which change in ‘Age 65+’ is reported as the largest standardised coefficient has especially increased in prominence in ‘Scottish Countryside’ from 5% of cells in 1991 to 20% in 2011. Generally in rural areas, change in this demographic group represents a greater influence on health outcomes (in terms of the largest standardised coefficient) than in urban areas where the contemporary rates of the percentage ‘Age 65+’ are reported as most influential. ‘London Cosmopolitan’ and ‘Business and Education’ centres have the youngest age profiles, implying that younger a decrease in ‘Age 65+’ in these area types is negatively associated with LLTI prevalence.

The importance of the ‘Not-UK born’ coefficient varies substantially across space but is not the most influential factor for any area types at either time point. Although not the most influential coefficient, the area type where ‘Not- UK born’ was the largest standardised coefficient for grid cells most frequently was ‘Prosperous England’. The ‘Not-UK born’ coefficient was generally shown to be least important in the area types where the highest rates of ‘Not-UK born’ populations are found within Britain including ‘London Cosmopolitan’. ‘Mining Heritage and Manufacturing’ has the lowest median percentages of not-UK born of all area classification types.

5.4 Discussion

The spatial approaches used in this thesis have revealed new insights about the drivers of geographical inequalities in health through correctly accounting for the spatial structure. Evidence presented provides a detailed picture of the spatial determinants of health inequalities and how they change through time.

5.4.1 The importance of utilising spatial models

Health Geography has been successful in re-establishing interest of the role of place in shaping health and health inequalities (Kearns and Moon, 2002). Several studies have documented a spatial gradient in health inequalities across Britain, but limited studies have examined this relationship using spatial analysis. Previous work has largely been based on the implied assumption that the relationship between contextual factors and health is spatially homogenous (Caughy et al., 2007). Global regression techniques model space as a discrete entity rather than a continuous parameter and do not account for the fact that place-related factors can be interconnected (Macintyre et al., 2002). Given the suggestion of spatial variance in explanatory variables established in Chapter 3 and Chapter 4, the application of GWR techniques were utilised to better understand spatial variability in the relationship between area deprivation and LLTI.

Results reveal clear disparities in the spatial structuring of the relationship between LLTI prevalence and area characteristics across Britain. Findings point to the need to understand the heterogeneity of area level determinants of LLTI across geographical areas. A focus on the local geographical distribution of inequalities reveals that focusing only on aggregate/national averages mask huge variations between areas, and fail to capture the complex relationship between poor health and its determinants at a small area level where individuals experience their daily lives. The range of R^2 values obtained from the GWR model confirm that a sensitivity to the local contextual characteristics of small areas is required to effectively understand and address health inequalities across Britain.

The results presented here confirm that a spatial approach, using a geographically detailed scale, facilitates an assessment of how far the populations of (parts of) Britain are becoming more or less similar. Evidence presented here as a result of the fine-scale geography utilised, suggests growing risks for the health and well-being of coastal (Depledge et al., 2017) and rural communities (Sabater et al., 2017). The coarser geographies and fixed administrative boundaries that have previously been used in many explorations of the geography of health inequalities have meant that distinctive, but often small coastal areas have habitually been overlooked. Additionally, the stratification of results here by area classification type demonstrates a need to engage more critically with localities beyond widely used urban-rural binaries. The distinctive local variation observed suggests that understanding the heterogeneity of area level determinants of LLTI across geographical areas is important; it can be misleading to generalise areas with similar contextual characteristics.

5.4.2 Enduring effects of concentrated disadvantage

The analysis demonstrates that each demographic and social determinant of health modelled are experienced differently across space with some factors more important in certain areas than others. It is clear from the evidence of small-area spatial variation and concentration of poor health presented by GWR that the sociodemographic contextual characteristics of the local neighbourhood environment need to be carefully considered when addressing persistent health inequalities across Britain. The results especially highlight the impact of employment status in producing distinctive spatial health inequalities. At both time points, the GWR model predicts poor health better in areas with higher unemployment rates such as postindustrial cities in northern England; for example Newcastle, Hull and Liverpool. As evidenced by explicit spatial patterning and the impact of previous unemployment rates being especially pronounced in deindustrialised areas of the country, this has particularly disadvantaged manufacturing communities. Results suggest that the long-term decline of core industries has been identified as important to the profound health and wellbeing challenges experienced in deindustrialised areas, creating a historical legacy of disadvantage. The former coalfields are a distinctive part of England and Wales and particularly highlight the effects of an unemployment legacy on health.

Considering socioeconomic attributes at a specific point in time and assessing the relationship to health in subsequent years, the influence of previous Census time point variables are shown to be important for contemporary health patterning. The results presented highlight that areas can also display persistent qualities. Linked to legacies of deindustrialisation, localised economic and social factors appear to have acted over time to amplify the effects of unemployment in the production of local rates of LLTI. Deindustrialised regions are characterised by an overall economic decline that has hindered regeneration and development of new economic pathways (Riva et al., 2011; Taulbut et al., 2014). It is this durability of character has patterned health disparities in space and over time, with deindustrialisation appearing to compound an already considerable health burden on the populations of heavy industry areas (Riva et al., 2011). In coastal areas deindustrialisation includes the decline of domestic tourism, but also fishing, ship building and port activities, has resulted in a relatively narrow industrial base and insecure, low paid and seasonal employment (Depledge et al., 2017). Evidence presented here implies that the distinct combination of industrial decline and geographical isolation has compounded difficulties. Not only do these areas themselves lack local job opportunities (Corfe, 2017) but travelling elsewhere for work is also relatively difficult (Simmonds, 2009).

Age is evidenced as being important to this relationship. Coastal localities are characterised by an older population, with the highest median rates for percentage 'Age 65+' recorded at both time

periods in 'Coast and Heritage' classified areas. In coastal areas change in the percentage of the population 'Age 65+' is an important factor. This is likely to result from in-migration for retirement, generally undertaken by those who are recently retired, usually relatively affluent and healthy, who seek a move for reasons of amenity and leisure (Sander and Bell, 2013). A potential result is an increased concentration of elderly people in an area who are likely to develop an LLTI as they age (Sabater et al., 2017). The importance of percentage 'Age 65+' in 'Mining Heritage and Manufacturing' area types is also evidenced in this investigation, with many grid cells in this classification reporting this demographic change to be the largest standardised coefficient at both time point. However, change in this age group is shown to be of comparatively slight importance. Literature suggests that people in these localities have fewer opportunities to move away and so people here are more likely to age in place (McCracken and Phillips, 2012; Sabater et al., 2017), with important implications for appropriate approaches to address health inequalities in these areas.

5.4.3 Limitations

The methodological and geographical approach of this research is novel and has provided new insights into understanding of the complexity of interconnection between local area deprivation and health. This research is, however, not without limitations. It should be considered that the area classification used in analysis refers to the most recent Census period (2011) and consequently, may not be fully applicable to all cells across all time points. Since the purpose of this analysis was to compare how the same areas changed over time it was not possible to apply separate area classifications for each time point. However, area deprivation has been demonstrated to tend towards persistence of advantage and disadvantage (Dorling et al., 2000). GWR has been critiqued for problems of collinearity amongst predictor variables (Wheeler and Tiefelsdorf, 2005), but is accepted as a useful exploratory tool that allows for an explicit spatial approach. There are also concerns about using aggregate level data to make generalisations about people and places (Openshaw, 1983), however this work specifically aimed to examine the influence of the neighbourhood environment upon health outcomes, therefore using individual level data would not be appropriate. Census data have been utilised through 1km² gridded cells to minimise generalisations, but allow an understanding of how geography matters for health at local level.

5.5 Conclusions

The study of the relationship between area-level factors and health is not new. However, the spatial variability across Britain in the determinants of health presented, highlight the importance of carefully considering the role of local context in producing health disparities at a geographically detailed scale. In addition to contributing original findings to the health

inequalities literature, the evidence reviewed has suggested a number of actions that have the potential to better address the causes of socioeconomic inequalities that underlie health disparities in Britain. Quantitative methods that model space explicitly remain under-utilised in place-based health research. The combination of data at a detailed spatial resolution that is explored with explicitly spatial methodologies has provided a detailed understanding of the changing spatial associations between deprivation and inequalities. The small scale focus of this research highlights how the relationship between variables differs with changing spatial scales and the impact this produces on health, demonstrating that geographical health divisions persist at a fine-grained, local scale. The demonstration of independent area-level effects in this investigation emphasises the need to focus on area-specific policy interventions which can be used to target specific predictors of poor health, for example (un)employment, that will be most effective at a local level. Geographical areas have different health experiences and therefore, where practical, future research and policy interventions should be sensitive to this.

To further enhance understanding of the complexity of interconnection between local area deprivation status and health, future research that focuses on exploring systematically long-term change over time in the deprivation and health status of small areas across Britain is needed. A detailed understanding of how inequalities manifest spatially is important for the success of initiatives to address them, both in terms of the specificities of the initiative themselves and their geographical targeting.

5.6 References

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Appendix B

Table 5.4 Descriptive statistics (raw percentage values 1991 and 2011)

Area Classification		Limiting Long Term Illness		Unemployment		Unemployment (previous Census)		Age 65+		Change in Age 65+		Change in car ownership		Not-UK born	
		1991	2011	1991	2011	1991	2011	1991	2011	1991	2011	1991	2011	1991	2011
Business and Education Centres	Median	12.42	17.79	10.70	7.45	11.58	6.38	16.28	14.95	-3.88	-0.81	-5.30	-1.22	6.25	12.92
	Minimum	0.97	3.69	0.00	0.00	0.00	0.00	0.32	0.48	-57.63	-19.58	-60.58	-50.61	0.40	0.74
	Maximum	30.55	42.84	46.35	28.48	51.32	29.59	51.19	46.08	60.11	20.37	33.87	56.26	50.79	73.46
Coast and Heritage	Median	11.4	19.18	7.00	4.64	7.88	4.16	18.63	21.82	-5.6	2.65	-6.17	-1.26	3.79	6.07
	Minimum	2.47	1.43	0.04	0.00	0.00	0.00	0.24	0.02	-53.92	-19.40	-34.28	-50.88	0.09	0.00
	Maximum	28.15	39.57	35.05	25.38	79.02	22.52	58.97	54.85	45.56	23.21	17.79	58.78	86.40	49.06
English and Welsh Countryside	Median	10.58	18.14	6.01	4.05	6.99	3.61	17.11	22.02	-5.81	3.58	-5.85	-1.69	3.03	4.47
	Minimum	0.03	2.54	0.00	0.00	0.00	0.00	0.17	0.07	-68.73	-32.33	-48.23	-49.98	0.00	0.00
	Maximum	33.9	51.04	54.61	34.07	70.35	27.58	68.92	70.24	46.76	30.55	33.28	45.58	80.77	83.06
London Cosmopolitan	Median	11.53	13.96	13.21	7.93	10.24	7.68	13.78	9.57	-3.73	-1.34	-4.38	4.26	25.46	41.24
	Minimum	3.49	5.24	2.03	1.64	3.32	2.18	2.34	1.78	-37.12	-14.37	-28.57	-20.92	4.70	11.64
	Maximum	21.15	25.22	31.07	17.59	24.35	18.58	29.86	22.34	42.08	5.65	18.00	48.77	59.97	68.03
Mining Heritage and Manufacturing	Median	12.75	20.19	8.99	6.37	11.01	5.33	15.05	17.96	-6.29	2.18	-6.68	-2.33	2.52	4.52
	Minimum	1.37	4.53	0.00	0.00	0.00	0.00	0.14	0.83	-62.5	-25.19	-44.26	-57.34	0.00	0.13
	Maximum	33.94	57.75	47.23	35.51	58.62	33.12	49.86	62.31	54.17	26.78	29.99	47.21	41.18	53.79
Prosperous England	Median	8.42	13.88	4.98	3.48	5.20	2.55	14.82	18.75	-5.4	3.42	-5.43	-1.30	5.74	8.49
	Minimum	0.92	2.25	0.00	0.00	0.00	0.00	0.12	0.18	-59.2	-16.96	-41.72	-54.38	0.00	0.24
	Maximum	34.58	58.53	20.24	18.69	77.83	15.28	78.62	77.09	50.63	35.56	23.76	54.95	88.97	86.24
Scottish Countryside	Median	10.43	19.27	8.25	6.18	10.13	5.73	14.63	18.42	-5.99	2.58	-6.08	-3.33	2.67	4.41
	Minimum	0.57	3.58	0.00	0.00	0.00	0.00	0.00	0.98	-72.75	-20.39	-45.03	-67.70	0.00	0.00
	Maximum	32.86	52.75	51.13	35.98	46.74	29.49	61.77	71.37	53.7	23.18	41.23	54.10	86.22	46.84
Suburban Traits	Median	9.81	15.52	7.59	6.19	7.62	4.44	14.64	15.58	-4.27	0.49	-4.90	-0.26	8.22	15.47
	Minimum	2.03	3.76	0.00	0.00	0.00	0.00	0.18	0.15	-55.26	-21.24	-40.50	-43.18	0.28	0.82
	Maximum	23.06	38.99	39.04	26.71	33.23	24.15	41.34	41.22	39.33	18.64	23.41	39.30	46.63	67.46
Total	Median	10.43	17.41	6.92	4.83	7.87	4.09	15.96	19.6	-5.61	2.71	-5.84	-1.59	4.21	6.83
	Minimum	0.03	1.41	0.00	0.00	0.00	0.00	0.00	0.02	-72.75	-32.33	-60.58	-67.70	0.00	0.00
	Maximum	34.58	58.53	54.61	35.98	79.00	33.12	78.62	77.09	60.11	35.56	41.23	58.78	88.97	86.24

Authors calculations using PopChange data derived from Office for National Statistics and National Records of Scotland.

Chapter 5: Exploring spatial variability in health inequalities across Britain in 1991 and 2011

Table 5.5 Descriptive statistics and largest (%) 1991 GWR standardised coefficients

Area Classification		1991 Standardised Coefficients						Cells (n)
		Unemployment	Unemployment (previous Census)	Age 65+	Change in Age 65+	Change in car ownership	Not-UK born	
Business and Education Centres	Median	0.60	0.21	0.53	0.11	-0.42	-0.23	2,868
	Minimum	-3.12	-3.16	-2.96	-6.37	-2.86	-2.84	
	Maximum	4.57	4.09	3.10	0.99	2.69	2.95	
	Largest Coefficient (%)	38	28	22	1	5	5	
Coast and Heritage	Median	-0.15	-0.07	-0.29	0.08	0.03	-0.35	3,231
	Minimum	-3.63	-4.70	-3.25	-6.24	-3.31	-3.50	
	Maximum	3.52	6.07	2.95	9.21	5.16	3.00	
	Largest Coefficient (%)	18	17	11	15	26	13	
English and Welsh Countryside	Median	-0.25	-0.16	-0.21	0.04	0.02	0.07	21,037
	Minimum	-4.53	-5.40	-5.47	-12.14	-6.67	-6.28	
	Maximum	5.17	4.79	4.46	13.91	7.28	4.45	
	Largest Coefficient (%)	15	15	13	14	24	19	
London Cosmopolitan	Median	1.05	0.09	0.61	0.10	-0.22	0.05	601
	Minimum	-1.26	-2.92	-1.58	-0.11	-1.93	-2.09	
	Maximum	3.58	2.94	2.63	0.38	1.55	1.40	
	Largest Coefficient (%)	50	19	24	0	1	5	
Mining Heritage and Manufacturing	Median	0.39	0.30	0.64	0.05	-0.36	0.08	8,566
	Minimum	-3.21	-3.29	-3.53	-8.45	-4.15	-5.22	
	Maximum	5.33	5.96	5.02	4.65	5.06	4.80	
	Largest Coefficient (%)	27	25	28	3	8	10	
Prosperous England	Median	-0.24	-0.29	-0.16	0.05	0.14	0.10	10,650
	Minimum	-5.72	-4.28	-3.76	-6.79	-3.93	-5.94	
	Maximum	3.53	3.29	3.64	8.52	5.89	3.74	
	Largest Coefficient (%)	15	11	13	11	28	22	
Scottish Countryside	Median	0.03	0.25	-0.10	-0.01	-0.03	-0.03	3,694
	Minimum	-2.62	-3.64	-3.60	-6.25	-3.66	-4.49	
	Maximum	3.15	4.49	3.81	4.23	3.27	2.67	
	Largest Coefficient (%)	21	28	14	5	19	12	
Suburban Traits	Median	0.37	0.08	0.28	0.07	-0.32	0.26	2,879
	Minimum	-2.93	-2.78	-2.88	-2.44	-2.37	-2.38	
	Maximum	2.93	2.89	2.84	5.01	3.76	3.36	
	Largest Coefficient (%)	33	19	18	2	10	18	
Total	Median	-0.04	-0.07	-0.01	0.06	-0.09	0.04	53,526
	Minimum	-5.72	-5.40	-5.47	-12.14	-6.67	-6.28	
	Maximum	5.33	6.07	5.02	13.91	7.28	4.80	
		100	100	100	100	100	100	

Authors calculations using PopChange data derived from Office for National Statistics and National Records of Scotland.

Chapter 5: Exploring spatial variability in health inequalities across Britain in 1991 and 2011

Table 5.6 Descriptive statistics and largest (%) 2011 GWR standardised coefficients

Area Classification		2011 Standardised Coefficients						Cells (n)
		Unemployment	Unemployment (previous Census)	Age 65+	Change in Age 65+	Change in car ownership	Not-UK born	
Business and Education Centres	Median	0.72	0.39	0.42	-0.18	-0.53	-0.28	2,868
	Minimum	-2.39	-2.36	-1.92	-3.10	-2.17	-2.69	
	Maximum	3.77	4.44	5.66	2.14	2.95	1.77	
	Largest Coefficient (%)	40	28	20	4	3	4	
Coast and Heritage	Median	0.02	-0.16	-0.23	0.02	0.04	-0.11	3,231
	Minimum	-2.69	-3.45	-3.18	-4.07	-3.19	-3.84	
	Maximum	3.16	3.79	3.89	4.60	5.00	2.83	
	Largest Coefficient (%)	20	15	10	17	20	17	
English and Welsh Countryside	Median	-0.28	-0.15	-0.14	0.06	0.10	0.02	21,037
	Minimum	-6.69	-6.60	-5.29	-4.85	-5.71	-5.06	
	Maximum	4.05	4.93	6.10	5.49	7.96	6.24	
	Largest Coefficient (%)	13	14	14	17	24	18	
London Cosmopolitan	Median	0.80	0.38	-0.05	0.63	-0.48	-0.48	601
	Minimum	-1.05	-3.64	-3.13	-1.90	-1.32	-3.66	
	Maximum	6.05	3.49	3.34	4.37	0.72	2.79	
	Largest Coefficient (%)	40	20	17	17	0	7	
Mining Heritage and Manufacturing	Median	0.53	0.32	0.37	-0.01	-0.39	-0.02	8,566
	Minimum	-2.69	-4.00	-4.70	-3.37	-3.62	-4.92	
	Maximum	4.38	4.51	4.92	4.08	5.28	3.14	
	Largest Coefficient (%)	32	26	19	9	5	10	
Prosperous England	Median	-0.33	-0.30	-0.18	-0.11	0.17	0.18	10,650
	Minimum	-3.74	-6.38	-5.30	-4.93	-5.00	-4.30	
	Maximum	3.10	5.31	4.01	9.58	4.85	5.06	
	Largest Coefficient (%)	12	9	13	13	29	24	
Scottish Countryside	Median	-0.11	0.16	0.07	0.18	-0.29	-0.07	3,694
	Minimum	-2.96	-2.22	-2.83	-4.49	-2.73	-3.37	
	Maximum	3.49	3.33	2.98	3.15	2.35	2.24	
	Largest Coefficient (%)	15	24	20	20	7	14	
Suburban Traits	Median	0.55	0.02	0.13	-0.01	-0.42	0.02	2,879
	Minimum	-2.44	-3.73	-2.96	-3.04	-3.16	-2.56	
	Maximum	3.22	4.10	3.31	3.72	3.24	3.24	
	Largest Coefficient (%)	40	17	15	10	8	10	
Total	Median	-0.03	-0.05	0.00	0.01	-0.11	0.00	53,526
	Minimum	-6.69	-6.60	-5.30	-4.93	-5.71	-5.06	
	Maximum	6.05	5.31	6.10	9.58	7.96	6.24	
		100	100	100	100	100	100	

Authors calculations using PopChange data derived from Office for National Statistics and National Records of Scotland.

Chapter 6

Conclusions

6.1 Introduction

The final chapter of this thesis begins by summarising its key contributions with respect to how the findings presented achieved the aims and objectives set out in Chapter 1. The limitations of the research are next acknowledged and strategies outlining how this work could be improved upon are discussed. Possible future extensions that build upon the ideas and contributions introduced in the thesis are then presented. The chapter ends with a concluding summary statement of the findings presented.

6.2 Key contributions

By recognising that relations between health and place have to be understood as a set of interrelated processes operating simultaneously at various spatial and temporal scales (Pearce, 2015; Lekkas et al., 2017), the work presented makes several key contributions. Specifically, the original contributions of this thesis lie in its use of existing Census data in a novel way to facilitate detailed spatial explorations of health inequalities across the entire population of Britain over a forty-year period.

6.2.1 Comparability over time

Although relational perspectives of place are widely recognised in the Health Geography literature (Pearce, 2015, Bambra et al., 2019), the majority of previous research that explores geographic variation in health has focused on cross-sectional analyses (e. g Macintyre et al., 1993; Diez-Roux and Mair, 2010; Dutey-Magni and Moon, 2016). There is limited understanding of how health inequalities have evolved and are influenced over much longer time series. This understanding is important given that places are in constant flux, changing with respect to historical trends that single points of time cannot fully capture. Single-point in time analyses may overlook processes of change or resilience that embed contemporary health and inequalities within locales (Lekkas et al., 2017). Using a temporal perspective and studying the development of the spatial arrangement of deprivation and health from 1971 to 2011, this thesis has adopted an approach for analysing the

spatial variability and mobility of health that builds upon the wealth of existing cross-sectional evidence.

The gridded ‘PopChange’ data on which this thesis is based, provides the first consistent small area Census dataset for Britain from 1971 to 2011 (Lloyd et al., 2016). As the size and shape of cells are consistent across all time points issues of inconsistent boundaries, that can hinder analysis of change over time, were removed and it was possible to generate directly comparable measures of areas allowing an assessment of how they have evolved over time. The potential for understanding long-term health and deprivation change offered through the use of a comparable Census dataset is highlighted by the novel findings presented within this thesis. Considering changes over time, the results highlight the enduring effect of historical conditions on health and provide insights into the extent to which area histories matter for health. For example, through the use of consistent data it has been possible to answer the substantive question of whether Britain has become more segregated by health status over time.

It has now been confirmed that there will be another United Kingdom (UK) Census in 2021 (Office for National Statistics [ONS], 2018) and it will be possible to extend the analyses to incorporate this additional time point when 2021 data from this Census become available. Findings presented in this thesis demonstrate the immense value the Census offers in exploring trends over time with an entire population coverage, however, concern remains that this could be the last Census (ONS, 2018). This study has reaffirmed the utility of Census data for research purposes; without Census data it would not have been possible to explore the changing spatial arrangement of health and deprivation for the whole of Britain over a long time period.

6.2.2 Detailed spatial resolution

Use of 1km² gridded ‘PopChange’ population surfaces (Lloyd et al., 2016; Lloyd et al., 2017) provide a very fine-scale spatial resolution. Such geographic detail is important to maximise understanding of the patterns and processes that exist within the changing spatial structure of health inequalities, as it allows more specific and detailed patterning to be uncovered. Many studies which seek to assess geographical divides are generally based on data for larger areas, including counties (Champion, 1989; Senior, 1998), wards (O’Reilly et al., 2005), local authority districts (LADs) and middle layer super output areas (MSOAs) (Duthey-Magni and Moon, 2016). A reduction in geographical detail is likely to correspond to a considerably diminished ability to assess how far the populations of (parts of) Britain are becoming more or less similar. In addition to providing detailed spatial resolution, the gridded population surface utilised allowed for a more natural representation of the spread of population across Britain with gaps where there is no population present; empty cells include, for example, large unpopulated areas in the highlands of Scotland

(Lloyd et al., 2017). A geographically-detailed approach, such as that achieved in this thesis through the use of gridded data, is revealing as it makes visible the residential locations in which people encounter regularly (and consequently, the scale at which individuals frequently encounter the various determinants of health).

By adopting a spatial perspective that utilises geographic data at a fine-scale resolution but with national coverage, this investigation explores the wider relational context of deprivation and health in a manner which does not lose the detail associated with studying small areas. In addition to fine-resolution gridded data, this is achieved through the use of explicit spatial modelling approaches. Quantitative methods that model space explicitly remain under-utilised in place-based health research despite theoretical and empirical understandings of the ecological influences on health being well established. The combination of data at a detailed spatial resolution that is explored with explicitly spatial methodologies has provided a detailed understanding of the changing spatial associations between deprivation and inequalities in health that was necessary to successfully address the aims and objectives of this thesis.

6.3 Research findings

Table 6.1 sets out where each of the thesis' aims and objectives were answered. Each aim is discussed in detail below.

Table 6.1: Framework of thesis aims and objectives

Aim	Objective	Relevant Chapter
I Explore the changing spatial structure of health in Britain 1991 to 2011	1 Review literature to comprehend the socioeconomic and geographical determinants of health, and their interdependence to (changing) health inequalities.	Chapter 2
	2 Determine the availability of consistent health and demographic data between 1971 and 2011	Chapters 3, 4 and 5
	3 Identify small scale geographical patterns of health for Britain	Chapter 3
	4 Examine how the patterning of LLTI has changed between 1991 and 2011	Chapter 3
II Understand the association between deprivation and spatial inequalities in health.	1 Review literature to comprehend the socioeconomic and geographical determinants of health, and their interdependence to (changing) health inequalities.	Chapter 2

III	Apply spatially explicit methods to disentangle the drivers of geographical inequalities in health.	2	Determine the availability of consistent health and demographic data between 1971 and 2011	Chapters 3, 4 and 4
		5	Explore the social and geographical determinants of health inequalities	Chapters 4 and 5
		1	Review literature to comprehend the socioeconomic and geographical determinants of health, and their interdependence to (changing) health inequalities.	Chapter 2
		2	Determine the availability of consistent health and demographic data between 1971 and 2011	Chapters 3, 4 and 4
		5	Explore the social and geographical determinants of health inequalities	Chapters 4 and 5
		7	Extend global regression approaches to incorporate a spatially explicit modelling framework	Chapters 4 and 5
		1	Review literature to comprehend the socioeconomic and geographical determinants of health, and their interdependence to (changing) health inequalities.	Chapter 2
		2	Determine the availability of consistent health and demographic data between 1971 and 2011	Chapters 3, 4 and 4
		6	Analyse the role of historical contextual factors in explaining contemporary health patterns.	Chapters 4 and 5
IV	Examine the importance of historical deprivation for the spatial patterning of health.	1	Review literature to comprehend the socioeconomic and geographical determinants of health, and their interdependence to (changing) health inequalities.	Chapter 2
		2	Determine the availability of consistent health and demographic data between 1971 and 2011	Chapters 3, 4 and 4
		6	Analyse the role of historical contextual factors in explaining contemporary health patterns.	Chapters 4 and 5

Aim I: Explore the changing spatial structure of health in Britain 1991-2011

A detailed knowledge of how health patterns have changed over time has allowed the identification of areas that have the greatest need for policy focus to reduce health inequalities. Chapter 3 explored how the population of Britain in 1991, 2001 and 2011 was spatially structured by Limiting, Long-Term Illness (LLTI). The results demonstrated distinctive spatial variability in LLTI rates and revealed intrinsic geographical differences in health inequalities across residential contexts. Broadly similar patterning over time is observed across Britain and it is noted that many coastal areas including Prestatyn, Ryhl, Fleetwood, Southend-on-Sea and Skegness have distinctly higher rates of LLTI. Examining health inequalities through an area classification framework provided new insights into changing health status in different demographic and socioeconomic contexts.

Through a novel analysis of change in self-reported health at a fine geographical scale, this thesis has focused on developing an understanding of the changing spatialities of health patterns in Britain. Between 1991 and 2011 there is an especially pronounced reduction in LLTI rates in urban centres, particularly in central London, Edinburgh, Cardiff, Manchester, Leeds and Sheffield with small increases in LLTI in surrounding suburban areas during this period. Some of the largest gains in LLTI rates are in coastal areas across Britain, with a distinctive patterning of higher rates in almost all populated areas along the coast. At all periods in time ‘Mining, Heritage and Manufacturing’ and ‘Coast and Heritage’ classified areas had the highest rates of LLTI of all area classification types. Although these area types have had consistently, comparatively high rates of LLTI over the twenty year period, the results showed that they have also experienced large increases over the period 1991 to 2011. Whilst overall LLTI rates are higher in the north of England, Wales and Scotland, differences between neighbourhoods are greater in southern regions of Britain. Within a trend of declining health segregation overall, ‘Coast and Heritage’ and ‘Business and Education Centres’ have become increasingly segregated. ‘Mining Heritage and Manufacturing’ areas have experienced the largest decrease in segregation over time. This decline has occurred consistently over the decades to become one of the least segregated area type by LLTI status.

As explored in Chapter 3, Moran’s I is a measure of spatial similarity and quantifies the degree of similarity of values to neighbouring values. The Index of Dissimilarity (D) is applied to assess the distribution (evenness) of characteristics in a population; the distribution of people who report a LLTI relative to those who do not. In Britain, overall decreasing evenness values (D), coupled with increased positive spatial association (I) suggests that neighbouring areas have become more similar in terms of health status. Table 6.2 illustrates the differing impacts of changing evenness and segregation outcomes. Health has become more distinctively spatially clustered over time; there has been a reduction in the distinction between areas characterised by poor or good health and greater spatial continuity of clusters so that sets of neighbourhoods together have similar health profiles.

Table 6.2: Interpreting changing evenness and segregation measures

	Increase in D	Decrease in D
Increase in I	<p>Increased unevenness of cells classified by good health or by poor health and reduced similarity between neighbouring cells.</p> <p><i>Poor health increases in poor health cells and good health increases in all/most other cells.</i></p>	<p>Increased group spread across cells and increased spatial similarity between neighbouring cells.</p> <p><i>Poor health spreads beyond existing clusters and increases in areas with previously good health. Large clusters of poor health or good health emerge.</i></p>
Decrease in I	<p>Increased unevenness of cells classified by good health or by poor health with decreased spatial similarity between neighbouring cells.</p> <p><i>Concentrations of good health and of poor health increase their share but neighbouring cells are less similar.</i></p>	<p>Decreased unevenness across cells and decreased spatial similarity between neighbouring cells.</p> <p><i>Poor health spreads out beyond clusters but there is a decrease in the concentration of poor health.</i></p>

In considering local areas using a long-term perspective, there is often a sense that they are constantly evolving. Whilst it is interesting to look at changing patterns of health, persistence in the spatial polarisation of health status is perhaps of greatest significance with respect to the impacts of changing public policy on health inequalities in Britain. Findings presented in Chapter 3 demonstrate the persistence of clusters of poor health. Persistent clustering of high rates of LLTI is found in traditional industrial mining areas such as south Wales, north east England, south Lancashire and the Yorkshire-Derbyshire-Nottinghamshire coalfield and of coastal localities popular with retirement migrants (Corfe, 2017) or transient low-income groups seeking affordable rental accommodation (Ward, 2015). Over the two decade period persistent clusters of low rates of LLTI are predominantly located in north east Scotland and across a wide band of inland southern England that aligns closely with ‘Prosperous England’ classified areas. Comparatively, areas classified as countryside or ‘Suburban Traits’ have experienced the least persistence of LLTI rates over time with potentially important implications for policy.

Aim II: Understand the association between deprivation and spatial inequalities in health

There is considerable evidence that socioeconomic deprivation has a damaging effect upon health (Diez-Roux and Mair, 2010; Bécares et al., 2012; Benzeval et al., 2014). The results presented in this thesis confirm that in seeking to explore the influence of place on health, understanding the role of deprivation is crucial.

Quantifying the complexity of deprivation and its influence on health was achieved through the use of a composite Townsend Index score (Townsend et al., 1988). Chapter 4 presents consistent evidence that small area deprivation is positively associated with the prevalence of LLTI health. The least deprived areas have the best health outcomes, and those with the most deprived circumstances have the poorest. A greater understanding of the interconnectedness of health outcomes and deprivation was obtained by additionally unpicking the relative contributions of unemployment, no access to a car, non-home ownership, and of household overcrowding. Unemployment is shown to matter significantly for health, with lower levels of unemployment linked to a decrease in the prevalence of LLTI. As evidenced in Chapter 4, unemployment fell between 1981 and 2011. Over the same period, the size of the unemployment coefficient (and association to LLTI) increased in effect size. An increase in LLTI prevalence associated with increased rates of ‘No Car or Van access’ is reported consistently over models across all time points and the effect size is shown to have remained fairly consistent over time despite increases in car ownership from 50% in 1971 to 75% by 2011. Results also demonstrate that at all time points the size of the effect of ‘Not Owner Occupied’ was small. Overcrowding is negatively associated with LLTI in 1991, but positively associated in 2001 and 2011. The areas with the largest increases in overcrowding between 1991 and 2001, and 2001 and 2011, have large populations of people from non-White ethnic groups and people born outside of the UK. Both of these demographic groups have younger age profiles than those who are White and also UK-born which might explain this finding.

The underlying demography of areas was important at each time point. Rates of being born outside of the UK were associated negatively with LLTI prevalence. This is an effect which appears to have strengthened over time as the percentage of not-UK born residents within Britain has increased. The age structure was also important. The percentage of young individuals (aged 14 or younger) was consistently negatively associated with LLTI reflecting that most chronic conditions are unlikely in younger populations (Chandola et al., 2007; ONS, 2014). The direction of the coefficient estimates regarding age groups are expected given well-established research on the association of morbidity and older age (Gould, 2009).

Aim III: Apply spatially explicit methods to disentangle the drivers of geographical inequalities in health

Health geography has been successful at re-establishing the role of place in shaping health and health inequalities (Kearns and Moon, 2002). Previous work however, has largely been based on the implied assumption that the relationship between contextual factors and health is spatially homogenous. The spatial approaches used in this thesis have revealed new insights about the drivers

of geographical inequalities in health through correctly accounting for spatial structure. Evidence presented throughout this thesis reveal a distinctive and spatially sensitive relationship between health and deprivation, detail that is disguised when using global models. Chapter 4 and Chapter 5 have utilised different spatial approaches to provide a more complete investigation to disentangle the drivers of geographical inequalities across Britain.

As established by the results presented in Chapter 4, the spatial dimension is an inherently important aspect of the relationship between LLTI prevalence and deprivation. Results demonstrated that model fit improved when spatial lag effects were considered. When the distance from the location of interest was taken into account, deprivation and demographic characteristics were found to explain a large proportion of LLTI variation across Britain. As demonstrated, correctly accounting for the spatial structure is beneficial to understanding health inequalities more effectively.

In Chapter 5, use of Geographically Weighted Regression (GWR) to explore non-stationary in the relationship between LLTI and selected covariates across Britain revealed how the effect of deprivation varied spatially. The GWR models reported R^2 values ranging from 0.03-0.97 (1991) and 0.03-0.98 (2011), suggesting that a sensitivity to the local contextual characteristics of small areas is required to appropriately understand and address health inequalities. For example, higher R^2 values were reported in different types of urban areas including: former industrial centres (e.g. Leeds, Sheffield, Sunderland, and Liverpool), mill towns (e.g. Bolton, Oldham and Bradford) and areas with coal mining heritage (e.g. Flintshire, Durham, Nottinghamshire and Newcastle upon Tyne). This is in contrast to large rural areas (e.g. Cumbria, north Wales, parts of Devon and Cornwall and areas of Northumberland) where model fit was lower, suggesting that the selected covariates were less relevant in these areas and more specific models are required to better understand health variation in these localities.

Utilising GWR also allowed an examination of the heterogeneity of area level determinants of LLTI across Britain. Results from Chapter 5 explored this in greater detail by examining what characteristics at the small-area level produced the largest standardised coefficient, and how these determinants were spatially distributed across Britain. A key finding of this analysis suggested that being unemployed matters more in certain localities and area types. In urban centres, particularly 'London Cosmopolitan', 'Business and Education Centres' and 'Mining Heritage and Manufacturing', unemployment coefficients were most frequently reported as the largest standardised coefficient.

The importance of employment for health is evident spatially though accessibility to labour market opportunities. Postindustrial decline is frequently cited as one of the major underlying reasons behind poor health profiles across Britain (Riva et al., 2011; Taulbut et al., 2014). The spatial models utilised in this thesis help to identify this as an important determinant for health inequality that would be otherwise missed. The spatial approach utilised highlights that isolated deindustrialised areas including coastal or rural mining communities have the worst health outcomes. Not only do these areas themselves lack job opportunities but travelling elsewhere for employment is likely to be relatively difficult (Simmonds, 2009).

Aim IV: Examine the importance of historical deprivation for the spatial patterning of health

As established in Chapter 2, urban sociology and human geography literatures have long recognised that neighbourhoods reflect broader, macro-level social and economic processes that have accumulated over many years and decades (Pearce, 2015; Bambra et al., 2019). The relational approach taken in this thesis, which incorporates historical dimensions is an important addition to this field of enquiry that enables a more complete understanding health inequalities. Through incorporating historical Census variables, this thesis offers a long-term approach to understanding how the longer-term drivers of health inequalities in Britain manifest spatially.

Findings presented in Chapters 4 and 5 highlighted that considering lag effects through time improved the model fit and demonstrated that socioeconomic context at previous Census points was predictive of health ten years later. A longer time-lag, extending beyond only the 10 years prior to the year of investigation was also considered but testing showed these longer-term relationships to be less revealing. One particularly pertinent potential driver for increasing geographical differences in health is the disparity in exposure to employment opportunities, especially in relation to the historical legacy of deindustrialisation. Across models, unemployment rates at the previous Census year had a strong positive relationship to LLTI prevalence. Spatially, this is especially pronounced in areas with industrial legacies, particularly localities with coal mining and manufacturing histories. Legacies of unemployment, rather than unemployment itself appear to be very important.

As identified when answering Aim I, clusters of poor health that have remained persistent over time are closely aligned with area type. ‘Mining Heritage and Manufacturing’ and ‘Coast and Heritage’ areas had the highest rate of persistently clustered LLTI grid cells over time. Such patterning implies the importance of historical area deprivation for spatial inequalities in health. Results presented in Chapters 4 and 5 highlight how localised economic and social factors may act over time to amplify the effects of deprivation for poor health. It is well established that traditional

deindustrialised areas have poorer health profiles and the long-term decline of core industries has been recognised as important to the profound health and well-being challenges experienced in areas with legacies of deindustrialisation including former mining areas, manufacturing localities and domestic tourism destinations (Riva et al., 2011; Taulbut et al., 2014).

The finding that area histories, particularly in relation to employment opportunities, continue to have an important influence in health status has implications for the ways in which widening health inequalities are approached and how interventions aimed at reducing inequalities across Britain are applied. Results demonstrate that the extent to which area history is found to matter for health changes through time with a spatial sensitivity to this relationship confirmed by the results. An explicitly spatial approach which incorporates area histories and explores how health at one point in time is influenced by conditions at a previous time point has offered a more complete understanding.

6.4 Implications

6.4.1 Wider processes of change and resilience

In line with the aims of this thesis, this work presents a detailed understanding of the changing spatial structure of health inequalities across Britain, the associations between deprivation and spatial inequalities in health and the importance of historical factors in shaping contemporary health inequalities.

The wider determinants of health, including housing, education, and employment, and the broader social structures in which they are embedded, are not experienced equally throughout Britain. A social gradient of health is well documented where, on average, at every point of the socioeconomic distribution, individuals have poorer health than those above them and better health than those below them (Benzeval et al, 2014). Evidence presented here also documents explicit spatial variability in health determinants with some factors found to be more pertinent for health in certain areas and at certain time points. As demonstrated here concentrations of disadvantage can have disproportionate effects upon the health of people exposed to them; inequalities matter most for certain people residing in certain localities, people who spend a greater period of their lives with poorer health than others.

Places are in constant-flux, changing with respect to historical trends and wider processes of social, economic, political and demographic change (Lekkas et al, 2017). As a result of this place characteristics differ markedly and results presented here suggest that such differences may have affected the impact of wider societal changes that have occurred across Britain over time. When exploring changing health inequalities it is important not to overlook processes of change or

resilience that embed contemporary health and inequalities within locales (Lekkas et al., 2017). Post-industrial decline, for example, is frequently cited as one of the major underlying reasons behind poor health profiles across Britain (Hacking et al., 2011; Audureau et al., 2013; Webber et al., 2015). The impact of deindustrialisation however, has not been experienced equally even within similar types of areas, and continues to contribute to differing health profiles across Britain. Clear spatial disparities in the extent to which being unemployed is worse for health are demonstrated in this thesis especially in relation to the historical legacy of deindustrialisation. Unemployment rates at the previous Census were found to be strongly associated with poor health outcomes - spatially this was especially pronounced in areas with coal mining or manufacturing legacies. It is important to recognise the unique health challenges faced by places. Developing methods for understanding the complex spatial structuring of health is important, especially for addressing spatial inequalities in health and for assessing the most appropriate scale at which to introduce interventions designed to improve health and create a more equal society.

6.4.2 Policy Implications

Social and spatial health polarisation is not inevitable and reducing persistent health gradients is an important social justice and economic policy objective in Britain (Public Health England [PHE], 2018). Despite this, a lack of understanding about how the spatialities of health change over time has previously challenged progress in delivering interventions. A detailed understanding of how inequalities manifest spatially is important for the success of initiatives to address them, both in terms of the nature of the initiatives and their geographical targeting. The policy implications of this gap in knowledge are marked, particularly as there is convincing evidence that inequalities across the social gradient of health are widening (PHE, 2018).

Area-based policies are a direct response to the contextual understanding that the area where you live can have a direct effect on your health. In order to develop effective policy intervention it is important to establish how geography matters for health. The focus of this thesis is exploring long-term changes in health and area deprivation at a geographically detailed scale across Britain. By recognising that relations between health and place have to be understood as a set of interrelated processes operating at various spatial and temporal scales, this work provides quantitative evidence that can be utilised to further enhance our understanding of the spatial complexity of health inequalities. In terms of health policy generally, an overarching message from the findings presented here is that geography matters.

Through the application of explicit spatial approaches analysis has made progress in understanding the heterogeneity of area level determinants at a fine geographical scale. Findings presented

demonstrate that determinants of health are experienced differently across space with some factors found to be more important in certain areas, and at certain times, than others. Such knowledge facilitates the targeting of policies in certain localities where they will have the most impact. The spatial variability of the relative influence of health determinants presented here, demonstrates the importance of considering the local context in health policy. One way to achieve spatially adaptive policies required is to relate policy to areas based on contextual similarities rather than ‘artificial’ administrative boundaries (Feuillet et al., 2015). It is important not to focus only on administrative boundaries; applying spatial methods has allowed the identification of common clusters of health outcomes which can be used as a basis for identifying areas for local health interventions based on similar contextual area characteristics.

The approach taken in this thesis incorporates area histories and explores how health at one time point is influenced by conditions at a previous point in time. Considering changes over time, results highlight the enduring effect of historical conditions on health and suggest that area histories are likely to matter more for health in certain areas. Developing from this finding, a key message to policy is that area based interventions should be informed not only by measures of deprivation for a given period, but also by conditions of the past – especially measures of change. Similarly, as findings demonstrate how health is influenced by area histories, there is a need for health policies to take a long-term approach. The long-term nature required for successful health inequality interventions may be overshadowed by short term priorities, but the evidence presented here demonstrates the value of taking a long-term approach.

Findings have demonstrated the importance of framing health through a perspective that embraces broader determinants including housing, education and employment. Policy making needs to focus on creating the conditions for people to live healthy lives, with population health as viewed as an asset that is influenced by policy (Bambra, 2010). In particular, the results presented here demonstrate exposure to employment opportunities to be especially influential in increasing geographical differences in health, particularly in relation to the historical legacy of deindustrialisation. The descriptive analysis of this thesis provides a useful starting point for teasing out causal mechanisms, but suggests that a focus on access to safe, rewarding and well-paid employment, especially in areas which are continuing to experience the enduring effects of deindustrialisation, is important for reducing the spatial gradient in health.

The findings presented in this thesis provide a comprehensive understanding into the spatial structure of health across Britain and how this changes across space and over time, perpetuated through wider socioeconomic and spatial inequalities. The spatial health inequalities highlighted in

this work demand a long-term approach across a breadth of systems; an outcome that is reflective of the complex reality though health is shaped over time. The potential impact of these policies may not be evenly spread across Britain or society, however by focussing on areas with the poorest health outcomes, especially areas experiencing persistent poor health, the greatest benefit will be achieved with the overall impact of reducing inequalities.

Focusing on policy implications, an interesting extension of this work would be to build upon the spatial evidence presented here and contribute to evidence-based policy by monitoring the impact over time of policies aimed at flattening health gradients. Given the spatial coverage of the findings presented this could be both nationally and also through the use of specific case-study areas where localised policies have been introduced. Similarly, it would also be insightful to explore the direct impact of wider political, economic and social changes that have taken place in Britain. For example, by linking the changing spatial patterning presented here to changes in government, changing trade agreements with EU countries, the growing accessibility of international travel or, at a more localised level, the closure of coal mines.

6.5 Limitations

The methodological and geographical approach of this research is novel and provides new insights into the complex relationships between deprivation and health. The potential for understanding long-term health and deprivation changes offered through the use of a comparable Census dataset has been highlighted by the novel findings presented here. There are, however, some caveats about the study design and thesis that are necessary to consider.

6.5.1 Geographical units

The comparable nature of the 'PopChange' data resource has allowed an in-depth assessment of how far (and over what scales) the population of Britain has been distributed by health and how this has changed over time. Without taking a consistent geographical approach to produce comparable results over time it would not have been possible to assess the extent to which change in health status is associated with area characteristics. The use of gridded data facilitated comparability over time as geographic zones are the same size and shape at all time points. Unlike many administrative data zones, gridded data are not constructed according to the population structure at any one time point and arguably represent population in a more natural way (Lloyd et al., 2017). Unlike standard areal data which tend to cover all land area in a study region, grids have a constant size and consequently their populations vary markedly, where there are no people, there may be no cells (Lloyd et al., 2017). For this reason a threshold approach was applied with analysis only conducted on cells which were estimated to contain people (in practice two separate population thresholds of 0.5 and 25 persons were applied) noting that fractions of people are possible when

utilising 'PopChange' data (Lloyd et al., 2016). Conducting analysis only on cells which were consistently populated across all study years provided a natural representation of the population of Britain but resulted in differing numbers of cells being used depending on the time points utilised in analysis (over how many time points cells needed to be consistently populated) and the specific population threshold applied. Experimentation suggested that results were robust to changes in thresholds.

The geographically detailed spatial information on health inequalities is achieved through the use of spatially and temporally consistent gridded data. However, such complexity can be difficult to interpret in detail, and geographical zones that do not conform to administrative areas can be problematic for area-based policies. In order to inform area-based policies effectively it may first be necessary to convert gridded data to appropriate area boundaries. Small area geographies can be merged in order to conform to higher administrative boundaries that are more appropriate for area-based intervention (for more information see Exeter et al. 2019), however, such an approach may introduce a small amount of further uncertainty to the 'PopChange' population estimates.

Using aggregated data and place-based approaches has limitations particularly in relation to the ecological fallacy. An ecological fallacy is a formal misconception in the interpretation of statistical data that occurs when inferences about the nature of individuals are deduced from inferences about the groups to which those individuals belong (Champion, 1989). Interpretation of the results presented here need to be made fairly to avoid erroneous generalisations. The purpose of this work was to provide a geographically rich analysis that was consistent over time, achieved through Census data. The fine-gridded data utilised provides a detailed investigation of health patterns and findings drawn from this thesis are still valid. The conclusions presented are useful to policy makers for assessing whether the population has become more or less similar over time and how it is geographically organised.

In any study that explores spatial patterns the Modifiable Areal Unit Problem (MAUP) must also be considered (Openshaw, 1983). Geographical space can be divided in an infinite number of ways. It may be that the areal units for which data are aggregated has intrinsic meaning about underlying populations and that the units are 'modifiable' (Lloyd, 2010). It is important to recognise that statistical analyses based on data aggregated over areas of different sizes will produce different results (Openshaw, 1983). Two sets of zones can have the same or similar areas but very different forms (Lloyd, 2010). The average experience may not accurately reflect the heterogeneity within that area and analysis of the same data can give very different results if they are aggregated to different modifiable areas (Boyle et al., 2004). The impact of the MAUP on this thesis' findings

were minimised by using the smallest available consistently sized units, but such impacts could be investigated through simple aggregation of the grid cells used in this investigation into different organisations to determine how the relationship between area deprivation and health inequalities is altered.

6.5.2 Census data

This thesis has utilised only Census data, which was the most appropriate data available to answer the aims of this investigation. Whilst the study had a clear rationale for the variables chosen, the range of variables was unescapably restricted to those that have been recorded consistently at successive Censuses. Census-based measures alone may be insufficient to capture the multiple pathways through which place can influence health inequalities. For example, the UK Census does not include a measure of income which could add valuable insights for measuring deprivation.

Changes to some Census questions asked included different definitions and outputs over time (Rees et al., 2002). Definitions of LLTI are not consistent across Censuses and the change of LLTI question wording probably resulted in wider reporting of age-related LLTI in 2001 that was not captured in 1991. Although there are some changes to Census questions over time, as Allik et al. (2016) note, the questions remain relatively consistent over time and across the constituent parts of Britain. Whilst the indicators used in this thesis are believed to be as time-robust as possible, changes to their relevance within society may have occurred over time particularly in relation to car ownership and owner-occupied housing as discussed specifically in relation to individual analysis sections and further in section 6.5.4 (page 171). Furthermore, the broad content of the Census may prompt respondents to confirm or deny poor health who might otherwise have responded differently in a more targeted survey, especially as it is self-completed (Rees et al., 2002).

It was not possible to utilise a high level of detail in the variables used. In line with ONS guidance (ONS, 2014) variables were harmonised in terms of variable detail so that outputs in 1971, 1981, 1991, 2001 and 2011 are directly comparable. To facilitate this comparability broad classifications such as White/non-White were used. While not ideal, the groupings used are the most detailed possible for the purposes of this analysis. Of course, had the groupings used been sub-divided there are likely to have been considerable differences between subsets. Further subdivisions of, for example, tenure, age, ethnicity and country of birth categories would allow a fuller assessment of the spatialities of poor health in Britain.

The comparable nature of the Census data offered through the ‘PopChange’ resource presents evidence of the changing spatialities of health across Britain that have not previously been

documented comprehensively. ‘PopChange’ data are generated by overlaying input source zones to output areas using postcode densities, as such the values for each cell are estimates (Lloyd et al., 2017). Whilst this method is accurate this is a limitation of the recourse which needs to be considered when interpreting results, however, as the grid cells used are 1km² the impact of estimating error is minimised (Lloyd et al., 2017). The use of this data brings a new and important perspective to debates about division, inequalities and the ways in which people in Britain live together or apart.

6.5.3 Subjective measure of health

Self-reported LLTI is used as the primary health outcome of the thesis. While the measure is widely used in existing research on health inequalities (Harding, 2003; Boyle et al., 2004; Norman et al., 2005; Norman et al., 2011), there are several issues with its use. Such measures are independent of any clinical diagnoses or assessment of severity (Kind et al., 1998). LLTI relies on a subjective assessment of health by an individual. As explored in Chapter 2, the concept of health is subject to different social and cultural perceptions of what constitutes health, and we all have an inherent grasp of what we believe health to mean for us as individuals (Hunt et al., 1991). Estimates of population health and reporting on inequalities according to subjective measures may consequently be biased through variations in interpretation of the questions over time or between cultures and by individuals. For example, gender differences in the reporting of subjective health are well documented with women consistently found to report poorer health status than evaluated through objective measures (Bora and Saikia, 2015; Boerma et al., 2016). The subjectivity of LLTI may introduce bias to the results presented within this thesis.

Despite these issues, there is a wide body of evidence that supports the validity of self-assessed measures of health, with a consistent association between self-rated health and objective health status well established (Jylha, 2009). Whilst objective diagnosis can confirm the state of poor health through the presence of disease, symptoms do not necessarily equate to poor health for an individual or unsatisfactory well-being (Huber et al., 2011). Self-reported measures are able to capture the impact of conditions that are poorly reflected by objective approaches including representing health experiences and expectations (Harding and Balarajan, 2000).

6.5.4 Measuring deprivation over time

The measurement of changing deprivation is challenging for several reasons. Firstly, the meaning of deprivation, and the relevance of Townsend input variables, changes over time. As the Townsend Index is a measure of relative poverty (Townsend et al., 1988), it was designed to capture area disadvantage compared to the rest of society. As society changes, so do the relative comparisons and therefore what constitutes deprivation will also evolve. This is problematic as the analyses

presented in this thesis required a measure that was comparable between 1971 and 2011, but remained meaningful at each time point. The nature of deprivation is unlikely to have remained constant over this forty year period. For example, Disney and Luo (2014) have demonstrated that the Conservative Government's 1980s 'right to buy' policy has increased levels of home ownership across Britain. Non-ownership measured at the 2011 Census is therefore likely to have a different meaning for deprivation than when measured at 1981 (Norman, 2010; Rees et al., 2002). Similarly, car ownership has become more accessible over time and resultantly 'no access to a car or van' in 2011 is likely to be reflective of very different socioeconomic circumstances than 'no access to a car or van' in 1991.

More sophisticated measures of deprivation such as the Index of Multiple Deprivation (IMD) have been developed over time that were unable to be included in the thesis. Utilising a more detailed measure of deprivation would have allowed the ranking of deprived areas as well as a detailed understanding of the association between deprivation and health (Department for Communities and Local Government, 2015). Whilst the IMD is composed of seven distinct domains which capture a broader range of relevant indicators when compared to the Townsend Index, not all inputs are available from Census data. Further, IMD domain methodology has changed between releases; they are not comparable between time periods (Smith et al., 2015). Further, with variants in England, Wales and Scotland the IMD does not permit comparison between constituent countries of Britain.

Whilst this thesis looks at changing deprivation over the long-term, the methodologies applied remain cross-sectional. The analyses fail to leverage the longitudinal element of the data which may limit the understanding of how and why deprivation matters for health. Though incorporating longitudinal methods would help to improve the quality of analyses, the limited number of Census time points (e.g. three time points where both health and deprivation data were available) meant that the scope of longitudinal methods would be limited and not always appropriate.

Additionally, it should also be noted that the area classification used in analysis refers to the most recent Census period (2011) and consequently, may not be fully applicable to all cells across all periods. Some grid cells may have changed their classification between Censuses which is not captured here. For example, suburban growth may mean that cells classified as 'Suburban' Traits' in 2011 may well have had characteristics twenty years earlier that would have been more appropriately classified as 'Countryside'. Since the purpose of this analysis was to explore how the same areas changed over time it was not possible to apply a separate area classification for each time point and results should be interpreted in consideration of this. However, area deprivation has

been demonstrated to tend towards persistence of advantage and disadvantage (Dorling et al., 2000).

6.5.5 Descriptive Analysis

Although the pervasiveness of the influence of material and social circumstances in determining health outcomes is recognised, a limitation of this thesis is that the analyses are mostly descriptive. The results identify important associations between health and deprivation, but do not provide understanding as to why these patterns are observed. The challenge of disentangling the causal mechanisms by which these determinants exert themselves on inequalities through a myriad of biological, behavioural, environmental and psychosocial pathways was not addressed. This was beyond the scope and aims of the thesis. The descriptive analysis presented in this thesis is pertinent to understanding why the spatial patterns observed matter for health inequalities and provides a valid and useful starting point for teasing out potential causal mechanisms. Interpretation of the results presented here should consider this. A future extension to the this thesis which focuses on teasing out the causal mechanisms though which deprivation influences health specifically is presented and discussed in further detail in section 6.5.3.

6.6 Future directions

The contributions of this thesis have opened up a number of exciting ways to build on the findings presented here and further improve understanding of health inequalities.

6.6.1 Greater applications of spatial modelling

There is considerable potential in applying spatial methods used here to other data. Many studies which tease apart the relationships between area characteristics and outcomes still use aspatial methods. Findings from this study have demonstrated that a spatial approach is invaluable and improves on common approaches such as Ordinary Least Squares (OLS) regression. Applications in Health Geography using GWR or spatial regression are uncommon, however most studies focus on understanding phenomena that are inherently spatial and therefore would benefit from modelling relationships with an explicit spatial component. The spatial methodologies utilised in this thesis can be applied to both area and individual level data, offering flexible approaches for improving understanding of the determinants of health processes. Rather than specifying a specific application or study, using the thesis as a springboard, the results advocate for greater incorporation of spatial models in studies. Each of the following three future directions outlined would be applied using the spatial approaches utilised in the thesis to help build more applications of their usage. Supplementing this strategy, producing short online resources that demonstrate how to incorporate spatial models into common analytical approaches (e.g. extending OLS regression to incorporate

spatial lags) would be also be valuable. The complementary combination of approaches will help to improve the uptake of spatial methods and minimise any skills gaps in researchers.

6.6.2 New gridded data

The potential for understanding long-term health and deprivation change offered through the use of comparable Census data has been highlighted. A natural extension to the initial findings presented would be to use areal interpolation weighting methods to convert objective health measures, such as hospital admissions records, into a gridded format. In this thesis health was operationalised through the presence or absence of subjectively recorded LLTI. Expanding health measures utilised to take account of objective assessments of health would provide insights into how the use of objective health data alters the association between health and deprivation, offering a more complete representation of the geographies of health needs and inequalities in Britain.

Gridded data permit the analysis of population change using spatially and temporally consistent geography and there is considerable potential in placing a wide array of datasets onto a common gridded geography (Lloyd et al., 2017). Grids allow for a straightforward assessment of change through time without using irregular zones as all units are of the same size and shape. An obvious benefit of population grids is that they can be easily compared to other grid models including ecological and environmental data to facilitate wider understanding of place effects on health. Despite these advantages, to inform area-based policies effectively gridded data may first require conversion to appropriate area boundaries. Exeter et al. (2019) provide a comprehensive overview of approaches to link small area geographies over time including methods for merging areas to conform to higher administrative boundaries. Whilst such conversion may make the findings presented here more easily applicable to area-based interventions, it is important not to overlook the value of geographically detailed spatial information. As discussed in 6.4.2 (page 166) work presented here demonstrates the value of spatially adaptive policies that relate to areas based on contextual similarities rather than ‘artificial’ administrative or statistical boundaries (Feuillet et al., 2015).

6.6.3 Explaining the role of deprivation

This thesis has advanced understanding of changing spatial inequalities in health. Results presented have demonstrated consistent spatial associations between deprivation and health outcomes. Further analyses are required to tease out the causal mechanisms through which deprivation change impacts upon changing spatial health outcomes. The findings presented in this thesis identified that areas with a legacy of deindustrialisation have higher rates of ill health than expected, understanding why this might be provides an important area type for future work to focus on. To advance discussion in the understanding of why these associations exist, taking a qualitative

approach in these areas to better understand what is happening and why these patterns have developed, is an important next step. It was not possible to find data on an exhaustive list of social, economic, political and cultural factors that may determine health outcomes within a specific area, and therefore taking a qualitative approach might help to explore the complex reasons behind the impact of deindustrialisation that would otherwise be hard to model. Such an approach would enrich understanding by providing valuable insights into factors linked to health outcomes such as social capital, shared histories and identity that are missing from this work but important for understanding how local particularities may mediate relationships.

To help identify causal mechanisms and avoid ecological fallacies, there is also a need to incorporate individual level data. To investigate sensitive neighbourhood effects for health during the life course Jivraj et al. (2019) use nationally representative individual data from two British birth cohort studies and link this to temporally constant neighbourhood boundaries. Such an approach has made it possible to follow people through places and over time, identifying whether there are particularly key time periods through the life course where area deprivation matters most for understanding later life (Jivraj et al, 2019). By taking this approach Jivraj et al. (2019) find that late-early-adulthood neighbourhood deprivation and midlife neighbourhood deprivation are more strongly related to mid-life health and wellbeing than other stages of the life course including adolescence. Building on this approach, it would also be insightful to link the ‘PopChange’ data utilised in this thesis to the 1970 British Cohort Study (BCS70) (Centre for Longitudinal Studies, 2016). The Cohort study follows individuals born in 1970 over their lives and collects detailed information including their health and social circumstances (Elliott and Shepherd, 2006). This would make it possible to follow people through places and over time, teasing out the pathways through which area deprivation ‘gets under the skin’ to shape health outcomes, including how area deprivation may mediate individual level risk factors such as occupation or ethnicity. An insightful extension would be to compare findings from this study with the work of Jivraj et al. (2019) to identify whether the additional precision of 1km² gridded units offered by ‘PopChange’ improve analyses compared to the larger geographic areas (middle layer super output areas [MSOAs]) utilised by Jivraj et al. (2019).

6.6.4 A Northern Ireland case study

Although population surfaces for Northern Ireland are not available as part of ‘PopChange’, data from the Northern Ireland Census of Population has been available as a standard gridded output since 1971 (Northern Ireland Statistics and Research Agency [NISRA], 2015). Over the past forty years Northern Ireland has experienced a very different socioeconomic, political and spatial landscape to that experienced in Britain, with rapid socioeconomic change and sectarian conflict (Doherty et al., 1997; Mesev et al., 2009). There is an extensive literature on various aspects of

segregation in Northern Ireland, particularly focused on residential segregation because of its close links to territoriality and politics (Mesev et al., 2009; Shuttleworth and Lloyd, 2009). There are no Census-based analyses of health inequalities and residential segregation that cover the entire 1971 to 2011 period using consistent geographical units through time for all of Northern Ireland. Extending the work presented in this thesis to incorporate data for Northern Ireland and exploring the changing spatialities of health in relation to these changing area characteristics would be an insightful development. Such an extension would allow the substantive issue of whether Northern Ireland has become more segregated by health status though time to be ascertained and would further illustrate how geography matters for health.

6.7 Concluding comments

In Britain, the opportunity to live a long a healthy life remains profoundly unequal and understanding persistent and increasing spatial inequalities in health is an important field of academic enquiry in geography. This thesis offers a new level of insight into the changing health and deprivation profiles of small areas in Britain. Analyses provide a detailed representation of the influence of deprivation for understanding health inequalities across Britain between 1991 and 2011. This thesis demonstrates that economic inequalities play a significant role in the divergent health profiles of different places and that the long-term socioeconomic history of local areas is especially salient for population health. Tackling these longstanding social and geographical injustices remains a key policy priority if health inequalities are to be appropriately addressed.

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Appendix C: Locations in Britain

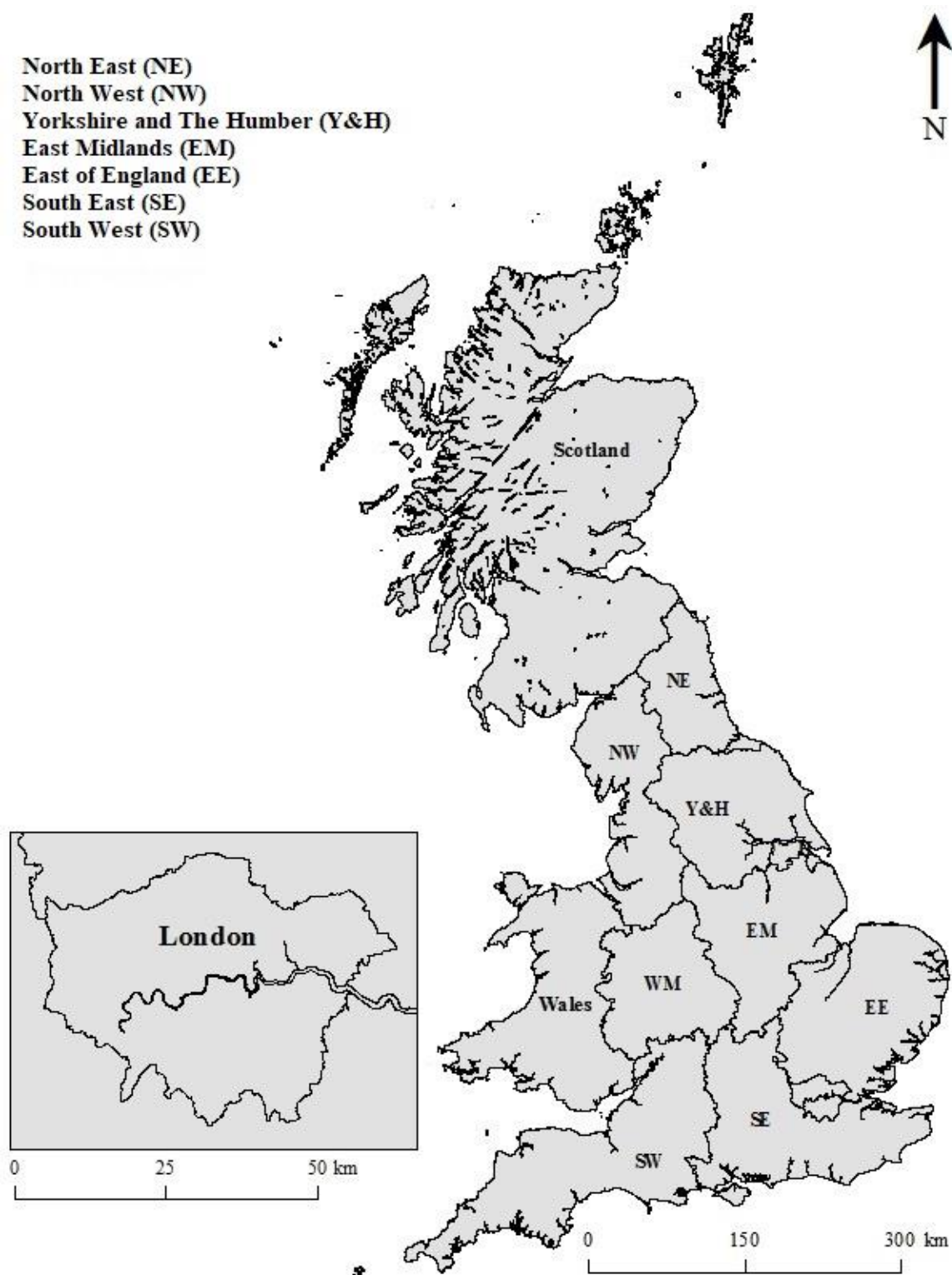


Figure C1 Location of constituent countries and regions in Britain



Figure C2 Location of key localities in Britain

Appendix D: Data Sources

Boundary Data

Office for National Statistics, 2011 Census: Digitised Boundary Data (England and Wales) [computer file]. UK Data Service Census Support. Downloaded from: <https://borders.ukdataservice.ac.uk/>

National Records of Scotland, 2011 Census: Digitised Boundary Data (Scotland) [computer file]. UK Data Service Census Support. Downloaded from: <https://borders.ukdataservice.ac.uk/>
This information is licensed under the terms of the Open Government Licence [<http://www.nationalarchives.gov.uk/doc/open-government-licence/version/3>].

Census Data

2011

Office for National Statistics; National Records of Scotland; Northern Ireland Statistics and Research Agency (2016): 2011 Census aggregate data. UK Data Service (Edition: June 2016). DOI: <http://dx.doi.org/10.5257/census/aggregate-2011-1>

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2001

Office for National Statistics (2011): 2001 Census aggregate data (Edition: May 2011). UK Data Service. DOI: <http://dx.doi.org/10.5257/census/aggregate-2001-2>

This information is licensed under the terms of the Open Government Licence [<http://www.nationalarchives.gov.uk/doc/open-government-licence/version/2>].

1991

Office of Population Censuses and Surveys; General Register Office for Scotland; Registrar General for Northern Ireland (1997): 1991 Census aggregate data. UK Data Service (Edition: 1997). DOI: <http://dx.doi.org/10.5257/census/aggregate-1991-1>

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1981

Office of Population Censuses and Surveys; Registrar General for Scotland (2000): 1981 Census aggregate data (Edition: 2000). UK Data Service. DOI: <http://dx.doi.org/10.5257/census/aggregate-1981-1>

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1971

Registrar General for England and Wales; General Register Office Scotland (2002): 1971 Census aggregate data. UK Data Service. DOI: <http://dx.doi.org/10.5257/census/aggregate-1971-1>

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Area Classification

2011 Area Classification for Local Authorities: Supergroups. Office for National Statistics: <https://webarchive.nationalarchives.gov.uk/20160114210846/http://www.ons.gov.uk/ons/guide-method/geography/products/area-classifications/ns-area-classifications/ns-2011-area-classifications/maps/index.html>

PopChange Lloyd, C. D., Catney, G., Singleton, A., Williamson, P., and Bearman, N., (2018). PopChange population grids for Britain, 1971-2011. [Data Collection]. Colchester, Essex: UK Data Archive. <https://popchange.liverpool.ac.uk>

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